Rationalizing Global Market Anomalies

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The Faculty of Economics, Business Administration and Information Technology of the University of Zurich hereby authorizes the printing of this Doctoral Thesis, without thereby giving any opinion on the views contained therein.

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In matters of style, swim with the current;
in matters of principle, stand like a rock.
(Thomas Jefferson)

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Chapter 1

Introduction

Financial market anomalies refer to the observation of anomalous patterns in asset prices that are hard to reconcile with standard economic theory. A cornerstone of financial markets theory is the efficient market hypothesis of Fama (1970) which essentially conjectures asset prices to reflect all available information. In its weakest form the efficient market hypothesis implies that any investment based on historical prices should not generate excess returns with respect to a given equilibrium asset pricing model. However, empirical evidence appears to be at odds with weak-form market efficiency: For instance, past winning stocks are found to deliver superior returns in the short run while past losing stocks subsequently continue to perform poorly. This rather simple momentum strategy represents a major financial market anomaly. Usually, the observation of such a market anomaly is rationalized by either risk-based or behavioral-based explanations; such explanations, however, are only meaningful if the respective anomaly is not spurious in the first place. We address the latter concern by testing for anomalous asset price patterns in different markets. If the respective anomaly also prevails in other markets we additionally corroborate the notion of a real anomaly.

In particular, we consider three distinct anomalies: The first anomaly originates from the accounting domain and is commonly referred to as the *accrual anomaly*. It has first been documented by Sloan (1996) and the related investment strategy essentially aims to identify mispriced companies by assessing their earnings quality as reflected in the amount of accruals. Second, we investigate the very *momentum effect*. Especially, we consider price and earnings momentum strategies, see Jegadeesh and Titman (1993) and Chan, Jegadeesh, and Lakonishok (1996); thus, we explore the idea whether stock prices exhibit short-term return continuation following the direction of past prices or analysts' earnings revisions. The third anomaly that we investigate is the *dispersion effect* of Diether, Malloy, and Scherbina (2002) who find that the dispersion of analysts' earnings forecasts helps predicting future returns.

To begin with, we screen for the accrual anomaly in several markets following the standard approach used in previous studies. Adjusting for common risk factors, we identify abnormal returns for nine countries in a sample of 29 developed equity markets. However, when a vast number of strategies is being tested around the globe, some strategies may excel by chance alone. Statistically speaking, there is a need to control for data snooping biases given the multitude of tests involved. While researchers have long been aware of data snooping biases, see Lo and MacKinlay (1990), Sullivan, Timmermann, and White (1999) and White (2000), common statistical procedures are not always optimal in terms of power, and hence they are most likely to reject any given anomaly. However, we aim to detect as many countries as possible where an anomaly actually exists. We therefore employ the recent proposal of Romano and Wolf (2005), which achieves improvements in power due to its stepwise nature and use of studentized test statistics.

These data snooping methods are first demonstrated by a thorough reinvestigation of the accrual anomaly. To see whether multiple testing procedures might be too conservative for return anomalies to show up in data sets with customary sample sizes, we also subject the international momentum effect to the very same procedures. While we substantiate the latter when properly accounting for multiple testing, the evidence for the accrual anomaly is rather spotty. Only for the U.S., the U.K., Thailand, and Switzerland do we reject the efficient market hypothesis, if we focus on the accrual-based hedge strategies' returns. Except for Switzerland these countries operate under common law, and thus their accounting systems potentially offer more flexibility with respect to accruals-driven earnings manipulation. Regardless of the mispricings' sources, we document a demise of the detected accrual anomalies, thereby adding to the evidence of diminishing market anomalies following their publication, see Schwert (2003).

With price and earnings momentum robustly defying capital market efficiency we reinforce the need for a sound explanation of the origins of momentum. In examining the link between both momentum anomalies we test the recent conjecture of Chordia and Shivakumar (2006) who claim that price momentum is merely a noisy proxy for earnings momentum in the U.S.. This explanation is intuitive since price momentum may well be rationalized in a model of investors underreacting to fundamental news as represented by earnings revisions. Along this line of reasoning we check whether this explanation constitutes a broad pattern in a large sample of 16

European countries. Our results are as follows: First, while we replicate the result of Chordia and Shivakumar (2006) for their sample period ending in 1999, the conjectured pattern has recently become more subtle. During the market frenzy at the end of the nineties, we observe a decoupling of price and earnings momentum in the U.S., which suggests that this period may be dominated by investors' over- instead of underreaction. Second, considering an aggregate European momentum strategy, we find that European price momentum appears to be a manifestation of earnings momentum throughout the whole twenty year sample period. Third, while we cannot replicate this argument in all European countries, there is considerable evidence that earnings momentum is a crucial determinant in explaining price momentum for most countries.

Having established a link between both anomalies we are still in need of a deeper momentum rationale. Since we cannot pinpoint a decent relation between momentum and macroeconomic risks, we suspect a behavioral-based explanation to be at work. In fact, we find momentum strategies to be most profitable when restricted to winner and loser portfolios characterized by proxies of high information uncertainty. In other words, the noisier the fundamental information, the slower its incorporation into prices, which is in accordance with underreaction of investors.

Regardless of the origins of momentum, be it risk or behavioral biases, it is most puzzling why this anomaly is not arbitraged away. Explaining this observation Korajczyk and Sadka (2004) and Lesmond, Schill, and Zhou (2004) detect trading costs to be the single most important impediment to successfully implementing momentum strategies in the U.S.. The amount of trading costs is not only driven by the huge turnover but also by liquidity risk, hence, Chordia, Goyal, Sadka, Sadka, and Shivakumar (2007) accordingly find the post-earnings-announcement drift to be confined to illiquid securities. Even more so, Liu (2006) constructs a liquidity-augmented asset pricing model that almost captures the abnormal returns of standard U.S. price momentum strategies. Extending this evidence, we find that international momentum strategies also work better when limited to stocks with high idiosyncratic risk or higher illiquidity, suggesting that limits to arbitrage deter rational investors from exploiting the anomaly.

While momentum is a longstanding asset pricing anomaly, we lastly investigate a more recent anomalous price pattern that has been discovered by Diether, Malloy, and Scherbina (2002) for the U.S. equity market. We find that stocks exhibiting high dispersion in analysts' earnings forecasts do not only underperform in the U.S. but also in some European countries. However, testing for the dispersion effect in many countries again calls for adequate multiple testing controls. Under this paradigm it turns out that none of the naïvely derived dispersion effects proves to be a sustainable phenomenon—not even the U.S. dispersion effect.

At first glance, this result is highly unexpected and we feel the need for an economic argument rationalizing the deficiencies inherent in the dispersion effects. A simple analysis of the time series nature of the dispersion effect reveals that the positive European return differentials amass in a very narrow time frame of three years, given a total sample period of twenty years. On the other hand, the U.S. dispersion effect provides a more favorable return pattern providing consistent abnormal returns most of the time. Still, the U.S. and the European dispersion strategy have a common characteristic in that they both have been very effective in hedging against the burst of the technology bubble. However, we question the practicability of the respective hedge strategy, because capturing the abnormal returns would have required short-selling of technology firms way before their stock price peaks. Hence, most investors following the dispersion strategy would have been squeezed out of the market by margin calls just before the strategy would have become profitable. Our observation that the latter bet appears to be the single driver of the naïvely derived return differentials therefore substantiates the doubts raised by our data snooping controls.

In further shaping intuition as to the dispersion effect's nature, we find it to be particularly pronounced among high and low dispersion stocks characterized by high information uncertainty as measured by analyst coverage or total stock volatility. In a related vein, Avramov, Chordia, Jostova, and Philipov (2008) find the U.S. dispersion effect to be only profitable among the worst-rated firms while it is non-existent for higher-rated firms. Likewise, Sadka and Scherbina (2007) show that analyst disagreement is closely related to trading costs in the U.S.. In particular, the mispricing is most severe for less liquid stocks. We corroborate this argument by documenting the highest mispricing when limiting the sample to stocks with high idiosyncratic volatility or to stocks subject to high illiquidity. This observation suggests that high arbitrage costs additionally deter investors from exploiting the dispersion effect.

To summarize, this thesis makes a strong case for using multiple testing procedures when several hypotheses are examined at once. Especially, investigating three distinct types of financial market anomalies we demonstrate mechanisms and merits of these recent procedures. Under this paradigm we find many anomalous asset price patterns to be more apparent than real and, likewise, equity markets to be more efficient than initially conjectured.

Chapter 2

The Accrual Anomaly

Judging a firm's financial strength typically reduces to some bottom-line numbers, of which earnings is the most important one. For earnings to represent a company's "real" periodic financial performance, accounting systems allow a company to record its economic transactions for a given reporting period. Firms decompose earnings into a cash flow and an accrual component. The accrual component gives the firm the flexibility to attribute earnings to the current period, even if those earnings have not yet been received in cash. Or the firm may reduce current earnings through depreciation expenses, although the corresponding cash transactions have been settled in some prior reporting period.

Even though accruals are not bad per se, they allow for substantial earnings management. Hence, accrual accounting may be abused, since any firm's management wants to provide solid and sustainable earnings. In the words of Dechow and Schrand (2004): "Manipulating accruals requires only a journal entry; manipulating cash flows requires collusion with other parties or manipulations of transactions and/or their timing." For instance, to boost earnings, managers could increase accounts receivable by prematurely recording sales, or they could understate liabilities, or both. Of course, heavy use of accrual accounting might trigger adverse earnings moves in the future, because the accrual component of earnings is less reliable than is the cash flow component. Therefore, low accruals may indicate high earnings quality, while high accruals may indicate low earnings quality.

Most investors and analysts focus on earnings when judging the profitability of firms. Therefore, it may well be that the additional information embedded in accruals goes unnoticed and that markets might be inefficient in processing accruals-related information. To exploit this inefficiency, going long in firms with low accruals and going short in those with high accruals is an obvious choice. Sloan (1996) documents abnormal returns of just such a hedge strategy in the U.S. equity market and various authors have confirmed his findings, subsequently referred to as the "accrual anomaly." For testing the robustness of the accrual anomaly it is straightforward to investigate whether it does carry over to other equity markets. Given the U.S. evidence and the literature on its potential causes, we can reasonably expect that some of these arguments, behavioral or institutional in nature, carry over to other equity markets even if accounting systems across the world are different.

2.1 Review of the Accrual Anomaly

To our knowledge, Sloan (1996) is the first author to document the accrual anomaly. He argues that investors do not correctly appreciate the information embedded in accruals, since they fixate on current earnings. To assess the impact of accrual accounting, Sloan decomposes earnings into the cash flow component and the accrual component. For computing the accrual component, Sloan uses the balance sheet method

$$\text{Accruals} = (\Delta\text{CA} - \Delta\text{Cash}) - (\Delta\text{CL} - \Delta\text{STD}) - \text{Dep}, \tag{2.1}$$

where ΔCA is the change in current assets, ΔCash is the change in cash and cash equivalents, ΔCL is the change in current liabilities, ΔSTD is the change in debt included in current liabilities, and Dep denotes depreciation and amortization expense.

2.1.1 Accrual Anomaly in the U.S.

Sloan (1996) provides empirical evidence that current earnings performance of U.S. companies is more persistent for companies with low levels of accruals. As a result, when forming their expectations on future earnings, investors tend to overweight accruals and are subsequently surprised when accruals turn out to be less persistent than expected. This overestimation of persistence in earnings that arise from accruals leads to abnormal positive returns for low accrual firms and abnormal negative returns for high accrual firms. As Sloan (1996) shows for the U.S. market, the excess returns of a hedge strategy based on accrual differences are statistically significant.

Following Sloan's (1996) original finding, numerous studies have been published in the financial economics and accounting literature, refining the measure of accruals by further decomposing the accruals component to disentangle the underlying mechanisms. For instance, Chan, Chan, Jegadeesh, and Lakonishok (2006) and Thomas and Zhang (2002) identify inventories and accounts receivable to be the main drivers of the accrual anomaly. Others relate the accrual anomaly to growth in net operating assets, e.g., Fairfield, Whisenant, and Yohn (2003) and Hirshleifer, Hou, Teoh, and Zhang (2004). Xie (2001) discovers that the mispricing is driven by abnormal accruals as measured in Jones (1991). These abnormal accruals are also known as discretionary accruals, suggesting that investors overprice accruals that are driven by earnings management. All of these studies provide evidence that the accrual anomaly is a stable and robust phenomenon in the U.S. equity market. Most recently, Hirshleifer, Hou, and Teoh (2008) find that the effect of accrual mispricing is reversed at the aggregate level. Aggregated accruals are a strong positive predictor of market returns, making the accrual anomaly even more of a puzzle.

The literature has offered various explanations to rationalize the accrual anomaly: Khan (2007) argues that the returns of the accrual-based hedge strategy compensate for bearing distress risk, since companies with extreme accruals typically have a higher risk of bankruptcy. Hirshleifer, Hou, and Teoh (2006) address these issues by considering a generic accrual risk factor. Although this factor works well when added to the standard Fama and French (1993) setting, one must be careful not to jump to conclusions. As Hirshleifer, Hou, and Teoh note the accrual factor can either capture risk or misvaluation. The authors further disentangle these effects and conclude that the accrual anomaly is not consistent with a standard rational asset-pricing framework.

Another line of research conjectures that the accrual anomaly is already subsumed by some other empirical anomaly. For instance, Desai, Rajgopal, and Venkatachalam (2004) find that the accrual anomaly vanishes when they control for value-glamour effects. However, this result only holds if the ratio of operating cash flow to price is the proxy for the value-glamour effect, which is rather uncommon in the finance community. More common proxies for the value-glamour effect, such as book-to-market, earnings-to-price, and cash flow-to-price, give different and inconclusive results. Collins and Hribar (2000) relate the accrual anomaly to the post-earnings announcement drift. Managers could use accruals to dampen the degree of earnings surprise. However, providing evidence that a combined strategy yields even more anomalous returns, Collins and Hribar conclude that both anomalies are distinct.

One may also wonder why the accrual anomaly is not arbitraged away. In explaining this observation Mashruwala, Rajgopal, and Shevlin (2006) state that exploiting the accruals' mispricing is risky and costly. Within extreme accruals portfolios they find small, low-volume stocks that have high arbitrage risk (which they measure by idiosyncratic risk arising from a standard market model). Thus, the accrual anomaly persists, since arbitrageurs cannot find close substitutes. Also, Mashruwala, Rajgopal, and Shevlin evidence that the returns to the hedge strategy are too volatile, which might force the arbitrageur to either increase the margin or liquidate the position.

Finally, Kraft, Leone, and Wasley (2006) argue that most of the accrual anomaly studies lack appropriate robustness tests and suffer from selection biases. They demonstrate the importance of robustness tests and suggest that the accrual anomaly is mostly driven by outliers. Therefore, their result poses a significant challenge to the question of whether investors truly fail to understand the low persistency accruals, as suggested by previous empirical research.

2.1.2 Accrual Anomaly—International Evidence

One way to test whether the U.S. accrual anomaly is just a statistical aberration or whether it deserves deeper reconsideration of its behavioral and institutional causes, is to use data from other countries. Following the line of reasoning presented in the first part of the previous section, we might indeed suspect that the accrual anomaly must also show up in other markets. However, in contrast to the U.S., evidence on the accrual anomaly in other countries is sparse and conflicting.

The study of Pincus, Rajgopal, and Venkatachalam (2007) is the first published international investigation that we know of. It is based on a sample of 20 developed countries gathered from Global Vantage and spans the period 1994 to 2003. The authors' findings support accrual anomalous returns in the U.S., the U.K., Canada, and Australia. They propose that the anomaly may be due to earnings management and barriers to arbitrage. Using country-level data, they contend that the accrual anomaly is more likely to occur in common-law countries, as opposed to code law countries. Common law countries allow extensive use of accrual accounting and have a lower concentration of share ownership and stronger shareholder protection. However, there are different and contradicting theories arguing that the accrual anomaly should be more or less pronounced in code law countries (e.g., Ball, Kothari, and Robin, 2000).

LaFond (2005) also examines whether the accrual anomaly is a global phenomenon and comes up with results that are different from those of Pincus, Rajgopal, and Venkatachalam (2007). Except for the U.S., LaFond (2005) uses data from Datastream/Worldscope over the 1989 to 2003 period. Within his sample of 17 developed countries, he finds the accrual anomaly in 15 countries. According to LaFond, the accrual anomaly is therefore not due to specific accounting measurement issues or any institutional country-specific characteristic, but to the general use of accrual accounting. Using the same database for the period of 1989-2004, the study of Liodakis, Brar, Gadaut, and Sharma (2004) supports LaFond's findings. These authors document high risk-adjusted performance of the accrual hedge strategy within a broad sample of European countries.

2.2 Data

We use a comprehensive sample of companies domiciled in 29 equity markets gathered from Datastream for the period from 1994 to 2007. We decompose earnings into the cash flow component and the accrual component. For earnings, we use the operating income that represents the difference between sales and total operating expenses. To compute the accrual component, we use the balance sheet method in equation (2.1) to ensure that our results are comparable to prior research studies such as that of Sloan (1996). In essence, accruals are changes in non-cash working capital less depreciation. To obtain the cash flow component, we take the difference between earnings and the accrual component. For comparison we standardize accruals, cash flows, and earnings by the company's total assets.

Table 2.1 contains information on the countries in our sample and the screening. We classify the countries according to their legal system, i.e., whether they share the common law or the code law legal tradition. We further categorize the code law countries as being of German, French, or Scandinavian legal origin. For each country, we collect companies by merging the live and dead research lists provided by Datastream on July 2nd, 2007. The latter lists comprise companies in extreme distress or those being merged, delisted, or converted; dead companies are included to avoid survivorship bias. The combination of all live and dead research lists gives an initial sample size of 99,591 companies.

To arrive at our final sample, we first adjust each country's list for secondary issues and cross-country listings to prevent double-counting. Second, we screen for non-equity issues that may still remain, i.e., we exclude investment trusts, ADRs, and the like. Third, we also exclude OTC stocks and stocks that are only listed on regional exchanges.

Table 2.1: Country Overview

The table contains descriptive information on the companies that have been domestically traded in the sample period (1994-2007). The screening of country lists depicts the evolution of the countries's samples. First, we give the *total* size of the country lists followed by the number of companies surviving the first screen for *major* listings. The column headed *final* contains the number of companies surviving the last screen eliminating regional listings and the like. FMV is the average free-floating market value in million USD. Using this metric we give the number of companies that exceed free-floating market values of 1000, 100 and 10 million USD. We further describe the sample of companies exceeding 10 million USD in free-floating market capitalization. We give the number of a country's dead companies (#Dead) and the number of companies with at least one accrual observation in the sample period (#Accruals), along with respective percentage values (%-Dead and %-Accruals). The last two columns give the earliest month with sufficient Fama-French data and the month of the filing deadline. The table provides information on common law countries in Panel A, while Panel B covers code law countries.

Country	Region	Screening of Country Lists			FMV	# Comps with FMV			Sample: FMV> 10				Dates	
		Total	*Major*	*Final*	Mio.	> 1000	> 100	> 10	#Dead	%-Dead	#Accruals	%-Accruals	FF	filing
Panel A: Common Law Countries														
USA	America	36659	20030	7279	1917	1495	4206	6272	2554	40.7%	4111	65.5%	Jul 92	3
Canada	America	12313	7919	2826	626	286	1161	2179	838	38.5%	1230	56.4%	May 89	4
Hong Kong	Asia	1299	1170	1106	734	109	457	947	87	9.2%	759	80.1%	Jun 97	6
Malaysia	Asia	1381	1272	1109	246	53	316	853	58	6.8%	707	82.9%	Jul 98	7
Thailand	Asia	920	678	647	296	39	212	540	94	17.4%	391	72.4%	Jul 98	3
Singapore	Asia	778	671	592	643	62	242	525	68	13.0%	433	82.5%	Feb 91	3
Australia	Australia	3807	2375	2096	583	149	585	1441	257	17.8%	1038	72.0%	Feb 91	4
New Zealand	Australia	505	246	209	321	18	79	166	50	30.1%	94	56.6%	Feb 91	4
United Kingdom	Europe	7677	3444	3232	1273	362	1135	2268	732	32.3%	1684	74.3%	May 89	6
Ireland	Europe	187	98	94	1580	23	56	85	26	30.6%	58	68.2%	Feb 91	6
India	Asia	3345	2668	2022	509	162	595	951	113	11.9%	515	54.2%	Jul 97	6
Panel B: Code Law Countries														
Germany	Europe	10740	1833	1525	1050	140	469	1017	228	22.4%	626	61.6%	May 89	8
Austria	Europe	360	177	161	857	23	70	119	31	26.1%	65	54.6%	May 89	6
Switzerland	Europe	1130	387	316	3589	74	211	277	49	17.7%	193	69.7%	May 89	6
Japan	Asia	4995	4706	3463	1297	562	1880	3172	315	9.9%	2712	85.5%	May 89	3
South Korea	Asia	2683	2102	2055	386	115	590	1740	134	7.7%	817	47.0%	Apr 00	6
Taiwan	Asia	984	905	794	693	98	496	730	60	8.2%	651	89.2%	Jun 97	4
France	Europe	2643	1458	1368	1778	161	459	945	258	27.3%	641	67.8%	May 89	6
Italy	Europe	794	390	365	2557	99	234	345	95	27.5%	248	71.9%	May 89	4
Greece	Europe	523	393	360	569	35	177	338	57	16.9%	265	78.4%	Jun 98	6
Indonesia	Asia	656	486	386	278	23	131	270	19	7.0%	181	67.0%	Mar 92	4
Spain	Europe	311	204	180	3744	65	138	170	51	30.0%	131	77.1%	Feb 92	6
Portugal	Europe	296	146	134	786	21	51	92	48	52.2%	59	64.1%	Jun 97	6
Netherlands	Europe	791	272	250	3543	68	136	201	77	38.3%	156	77.6%	May 89	5
Belgium	Europe	1000	288	263	1164	39	110	206	40	19.4%	110	53.4%	May 89	6
Sweden	Europe	1203	549	441	1011	58	198	346	109	31.5%	273	78.9%	May 89	6
Norway	Europe	585	328	284	712	32	154	254	98	38.6%	194	76.4%	May 89	6
Denmark	Europe	685	365	230	761	32	118	197	55	27.9%	123	62.4%	May 89	6
Finland	Europe	341	190	180	1535	37	96	159	42	26.4%	131	82.4%	Mar 91	6
	All	99591	55750	33967	1199	4440	14762	26805	6643	32.9%	18596	69.4%		

We further exclude those having market capitalization below 10 million USD. While these adjustments impact all country lists, the effect is most pronounced for the U.S., where the final country list is restricted to stocks listed on NYSE, AMEX, and NASDAQ. We further exclude those companies from the sample that either have missing data in any of the above financial statement variables, or for which we cannot compute the accruals, or both. These are mostly financial companies, for which accruals are not very meaningful figures. Our final sample comprises 18,596 companies. Table 2.2 summarizes the number of companies with accrual levels by country and year. The majority of firm-year observations is concentrated in the U.S. (32,282), Japan (22,941), and the U.K. (11,461). The total of firm-year observations is 132,493. When restricted to the time period and countries used in prior studies, our universe is smaller than that of LaFond (2005) (77,571 compared to 130,188 firm-years) and slightly larger than the one of Pincus, Rajgopal, and Venkatachalam (2007) (70,359 compared to 62,027 firm-years). Note that we exclude 0.37% of firm-years due to observations with absurd accruals, i.e., the absolute value of the ratio of accruals to total assets exceeds one.

2.2.1 Return Data

Ince and Porter (2006) show that one cannot detect the U.S. momentum effect using raw Datastream data. Comparing Datastream with the CRSP tapes, they develop a set of rules that enables researchers to nonetheless obtain valid statistical inference from the Datastream database. In particular, they propose two major adjustments. One is to remove non-common equity from the respective country research lists and the other is to screen for irregular return patterns. Since we have already dealt with the former when deleting preferred stock and other secondary issues, we only have to address the quality of return data by following the suggestions of Ince and Porter. We consider monthly local currency stock returns inclusive of dividends by using total return figures. To represent the respective markets, we use common indexes. For instance, we choose the MSCI USA for the U.S. and for Japan we choose the TOPIX. Three-month T-bills of the respective countries serve as the risk-free rates.

Table 2.3 demonstrates the effectiveness of our screening endeavors. Panel A gives an overview of the return data screening on country level, i.e., we track the total number of changes made per country in absolute and relative terms. For instance, the U.S. requires to change 0.07% of return observations which represents the smallest figure in the sample, while Switzerland is at the other end of the scale with 0.85%. This figure is on average 0.33% across all countries.

Table 2.2: Companies with Accruals

The table displays the number of companies for which accruals can be computed for a given year. The two rightmost columns give the amount of absurd accruals, i.e., observations where the absolute value of the ratio of accruals to total assets exceeds one. Panel A covers common law countries and Panel B covers code law countries.

Country/Year	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	Σ #firm years	*Absurd Accruals* absolute	relative
Panel A: Common Law Countries																
USA	1221	1317	1800	2015	2354	2750	3248	3145	2987	2920	2924	2883	2818	32382	111	0.34%
Canada	209	224	231	275	306	343	521	602	653	703	789	831	851	6538	36	0.55%
Hong Kong	69	73	99	161	224	249	253	277	414	552	643	705	715	4434	57	1.29%
Malaysia	118	121	139	201	225	252	260	279	405	477	509	578	645	4209	18	0.43%
Thailand	104	139	149	164	182	195	194	194	274	270	313	344	350	2872	14	0.49%
Singapore	61	63	80	120	135	145	150	168	237	285	326	357	389	2516	13	0.52%
Australia	98	100	113	144	175	187	223	286	399	625	668	732	834	4584	69	1.51%
New Zealand	17	17	26	33	40	45	47	51	54	62	65	69	71	597	4	0.67%
UK	581	606	637	656	841	924	950	928	942	999	1061	1148	1188	11461	57	0.50%
Ireland	29	31	32	32	42	44	46	46	46	46	45	44	45	528	2	0.38%
India	80	96	107	173	195	212	218	219	260	306	319	377	449	3011	4	0.13%
Panel B: Code Law Countries																
Germany	209	242	251	255	341	431	469	476	491	469	487	492	479	5092	18	0.35%
Austria	20	25	33	33	39	48	51	53	54	51	50	47	46	550	1	0.18%
Switzerland	84	92	99	108	135	146	146	150	159	162	168	168	161	1778	0	0.00%
Japan	843	882	787	1460	1528	1542	1662	2166	2284	2406	2429	2461	2491	22941	7	0.03%
South Korea	28	53	140	161	199	241	325	514	570	636	732	755	770	5124	21	0.41%
Taiwan	22	37	87	162	180	193	198	308	397	610	627	632	630	4083	1	0.02%
France	215	233	241	259	348	406	457	476	477	463	476	476	477	5004	14	0.28%
Italy	81	83	93	99	120	147	167	182	190	191	198	202	196	1949	2	0.10%
Greece	65	75	79	78	108	123	134	167	197	214	208	205	205	1858	2	0.11%
Indonesia	47	51	53	76	86	91	92	107	147	160	167	166	171	1414	5	0.35%
Spain	64	66	68	72	90	92	99	102	105	102	102	105	99	1166	0	0.00%
Portugal	24	25	30	34	46	42	44	42	42	40	39	37	34	479	1	0.21%
Netherlands	96	101	103	106	128	146	145	126	120	117	113	112	103	1516	8	0.53%
Belgium	43	46	49	51	69	85	87	85	84	83	87	86	86	941	2	0.21%
Sweden	64	74	85	92	139	174	189	188	186	185	196	206	194	1972	10	0.51%
Norway	48	55	57	61	110	121	123	100	102	105	115	124	119	1240	2	0.16%
Denmark	70	72	75	77	95	104	107	99	94	93	93	89	87	1155	6	0.52%
Finland	50	56	58	59	79	96	99	98	104	103	98	99	100	1099	2	0.18%
Σ	4660	5055	5801	7217	8559	9574	10704	11634	12474	13435	14047	14530	14803	132493	487	0.37%

2.2.2 Assessment of Data Quality

To measure the increase in data quality, we first use raw Datastream data to compute the correlation between an equally weighted portfolio and a broad market index of the respective country. Then we compare the initial correlation to the correlation that we obtain using cleaned Datastream data. For Canada, Ireland, Spain and the Netherlands, the results are especially startling. The initial return correlation of the respective market index with an equally weighted portfolio comprising all stocks is close to zero. Using the adjusted data correlations exceed 0.7 in all three cases.

However, data screening is also important for the remaining countries. For 15 countries we achieve correlation gains greater than 0.15, and for ten countries the gains exceed 0.4, giving rise to correlations around 0.7 or well above for almost all countries. We note that the return issues concentrate in smaller-size companies, since the gains in correlation are more moderate when we use only the largest 10% of companies as a benchmark. Only for India and Indonesia do we fail to obtain reasonable correlation figures after cleaning.

To further demonstrate the quality of the adjusted database, we check for the well-known price momentum effect before and after screening. Price momentum refers to the observation that past winning stocks continue to deliver superior returns in the short run while past losing stocks subsequently continue to disappoint. Particularly, we compute the momentum-factor by using a standard approach, i.e., each month we rank a country's stocks according to their previous 12-month performance. The returns of the momentum strategy are then given by the returns of a portfolio that is long in the winner quintile and short in the loser quintile of each month. At first glance, inferences do not appear to be severely impacted when using raw data. Our analysis reveals significant returns for 14 (15) countries at the 5% (10%)-level for the raw data while we obtain 17 (20) countries with significant returns in the case of cleaned data. However, among the 29 test statistics, 16 do experience a change in terms of statistical significance before and after cleaning. In particular, using raw return data does not indicate a momentum effect for the U.S. and falsely detects an Asian momentum effect while missing several European momentum anomalies. After cleaning, the momentum effect for the U.S. is statistically significant. Hence, using the cleaned database provides evidence that is consistent with prior results on international momentum strategies as documented by Rouwenhorst (1998) or Griffin, Ji, and Martin (2003, 2005).

Table 2.3: Cleaning of Return Data

Panel A records the total changes made to the return data in absolute and relative terms. In Panel B, we compare the correlation of an equally-weighted portfolio to a broad market index before and after data cleaning, using all stocks or a portfolio of the country's top ten %. Panel C reports average monthly buy-and-hold returns to price momentum portfolios with t-statistics in bold face if significant at 5% and in italics if significant at 10%. Data are from May 1994 to February 2007.

	A: Issues	*B: Sanity Correlation Check*				*C: Momentum*			
Country	Σ	Portfolio	*Correlation*			*Before*		*After*	
			initial	final		Hi-Lo	t-stat	Hi-Lo	t-stat
USA	694	all stocks	0.609	0.750	Return	-0.009	-0.65	0.013	**2.67**
	0.07%	top ten%	0.875	0.897	Volatility	0.168		0.061	
Canada	356	all stocks	0.049	0.728	Return	-0.004	-0.33	0.010	**2.57**
	0.11%	top ten%	0.726	0.778	Volatility	0.132		0.049	
Hong Kong	413	all stocks	0.413	0.578	Return	0.018	**2.23**	0.007	1.51
	0.28%	top ten%	0.753	0.784	Volatility	0.102		0.059	
Malaysia	119	all stocks	0.844	0.847	Return	0.006	0.91	0.004	0.68
	0.09%	top ten%	0.906	0.923	Volatility	0.080		0.069	
Thailand	490	all stocks	0.627	0.750	Return	0.024	**2.33**	0.006	0.93
	0.59%	top ten%	0.550	0.916	Volatility	0.129		0.085	
Singapore	60	all stocks	0.785	0.789	Return	0.010	*1.95*	0.007	1.52
	0.07%	top ten%	0.878	0.892	Volatility	0.064		0.061	
Australia	273	all stocks	0.475	0.617	Return	-0.003	-0.39	0.006	*1.71*
	0.12%	top ten%	0.218	0.869	Volatility	0.087		0.047	
New Zealand	33	all stocks	0.660	0.697	Return	0.012	**2.27**	0.010	**2.48**
	0.13%	top ten%	0.571	0.838	Volatility	0.068		0.050	
UK	364	all stocks	0.594	0.664	Return	0.018	**4.92**	0.014	**4.43**
	0.10%	top ten%	0.825	0.843	Volatility	0.046		0.040	
Ireland	21	all stocks	0.049	0.703	Return	0.020	**2.27**	0.010	*1.77*
	0.16%	top ten%	0.786	0.786	Volatility	0.110		0.068	
India	500	all stocks	-0.024	-0.027	Return	-0.007	-0.18	0.014	**3.12**
	0.34%	top ten%	-0.010	-0.020	Volatility	0.469		0.058	
Germany	855	all stocks	0.267	0.725	Return	0.124	1.63	0.016	**3.65**
	0.55%	top ten%	0.397	0.867	Volatility	0.946		0.054	
Austria	66	all stocks	0.188	0.784	Return	0.015	1.42	0.005	*1.75*
	0.36%	top ten%	-0.061	0.799	Volatility	0.133		0.036	
Switzerland	361	all stocks	0.322	0.806	Return	0.029	**2.95**	0.015	**3.77**
	0.85%	top ten%	0.108	0.848	Volatility	0.122		0.049	
Japan	403	all stocks	0.623	0.743	Return	0.014	**2.17**	0.002	0.50
	0.08%	top ten%	0.329	0.876	Volatility	0.082		0.047	
South Korea	1490	all stocks	0.660	0.723	Return	0.029	**2.16**	0.003	0.37
	0.56%	top ten%	0.859	0.879	Volatility	0.168		0.093	
Taiwan	6	all stocks	0.848	0.849	Return	-0.001	-0.22	0.001	0.16
	0.01%	top ten%	0.933	0.933	Volatility	0.073		0.068	
France	590	all stocks	0.323	0.729	Return	0.092	1.45	0.012	**3.09**
	0.41%	top ten%	0.632	0.869	Volatility	0.790		0.049	
Italy	66	all stocks	0.779	0.856	Return	0.016	**2.94**	0.011	**2.57**
	0.12%	top ten%	0.752	0.919	Volatility	0.067		0.053	
Greece	117	all stocks	0.335	0.556	Return	0.027	**2.96**	0.016	**2.85**
	0.22%	top ten%	0.595	0.710	Volatility	0.115		0.071	
Indonesia	183	all stocks	-0.018	-0.128	Return	0.015	1.55	-0.002	-0.29
	0.44%	top ten%	-0.184	-0.177	Volatility	0.119		0.091	
Spain	153	all stocks	0.031	0.804	Return	0.035	**2.49**	0.012	**2.92**
	0.58%	top ten%	-0.030	0.688	Volatility	0.174		0.052	
Portugal	108	all stocks	0.520	0.678	Return	0.005	0.04	0.008	1.48
	0.76%	top ten%	0.293	0.859	Volatility	1.334		0.065	
Netherlands	121	all stocks	0.086	0.768	Return	0.255	1.09	0.021	**4.36**
	0.39%	top ten%	0.577	0.759	Volatility	2.911		0.059	
Belgium	117	all stocks	0.140	0.811	Return	0.007	0.16	0.015	**4.44**
	0.37%	top ten%	0.091	0.910	Volatility	0.560		0.041	
Sweden	221	all stocks	0.319	0.772	Return	-0.013	-0.27	0.021	**3.67**
	0.41%	top ten%	0.636	0.812	Volatility	0.572		0.073	
Norway	112	all stocks	0.633	0.750	Return	0.023	**2.84**	0.021	**3.98**
	0.29%	top ten%	0.509	0.729	Volatility	0.103		0.065	
Denmark	233	all stocks	0.071	0.619	Return	0.064	**2.12**	0.012	**3.98**
	0.77%	top ten%	0.353	0.777	Volatility	0.373		0.037	
Finland	97	all stocks	0.709	0.721	Return	0.036	**3.86**	0.019	**4.24**
	0.40%	top ten%	0.628	0.758	Volatility	0.116		0.055	

2.3 The Traditional Route to the Accrual Anomaly

To quantify the accrual anomaly, we take the traditional approach and construct a hedge strategy that is long in low accruals companies and short in high accruals companies. We fix the holding period of companies in the hedge strategy to one year, following the filing deadline of the respective fiscal year end. Hence, we assume a given firms' financial statements to be publicly available at that time. Since the companies' reporting periods do not necessarily coincide, we rank companies by their annual accrual levels on a monthly basis. By doing so, we can react as fast as possible to any given accruals signal.[1] Each month, we build a portfolio that is long in the lowest and short in the highest accruals quintile. We do not require companies to have accruals figures for the subsequent year. Therefore, we circumvent the look-ahead bias of other studies, as reported in Kraft, Leone, and Wasley (2006).

2.3.1 Risk and Return

Table 2.4 reports equally weighted monthly mean returns on buy-and-hold quintile portfolios built yearly according to their level of accruals. For half of the countries, the extreme quintile portfolios are the riskiest in terms of volatility. The remaining quintile portfolios usually exhibit less volatility. However, the other half of the countries is characterized by volatility figures that are almost identical across quintiles.

To assess the profitability of the hedge strategy, we consider the return differential along with its t-statistic. Using this metric, we identify eight out of 29 countries that have anomalous accrual returns on a 5% level or better. The eight countries are the U.S., the U.K., Thailand, Japan, Germany, Switzerland, France, and Denmark. If we relax the significance level to 10%, no additional country appears to be anomalous.

Concerning the nine suspicious countries we note that the accruals screen is sometimes useful for detecting overvalued companies or undervalued companies, or both. Hence, sometimes both extreme accrual quintile portfolios appear to be mispriced. In this context, Chan, Chan, Jegadeesh, and Lakonishok (2006) argue that if managers are manipulating earnings, they will most likely opt for higher earnings figures instead of lower ones. As a consequence, the poor performance of the highest accruals quintile is the most likely driver of a given accrual anomaly.

[1] Alternatively, we can rank companies by their accrual levels on a yearly basis. For a given year, we would obviously require all companies' balance sheet data, i.e., we would have to wait up to the filing deadline following fiscal year end. By then, it may well be that any accruals signal induced by companies reporting before calendar year end is already rendered useless.

Table 2.4: Returns of Accruals Quintile Portfolios

The table gives average monthly buy-and-hold returns to quintile portfolios that are built monthly dependent on the level of accruals. We give the return differential of a portfolio long in the lowest accruals quintile and short in the highest accruals quintile along with the according t-statistic that is in in bold face if significant on a 5%-level or in italics if significant on a 10%-level. All figures refer to the period from May 1994 to February 2007.

		Portfolio Accrual Ranking						
Country		Lowest	2	3	4	Highest	Lo-Hi	t-stat
USA	Return	0.032	0.024	0.022	0.020	0.022	0.010	**5.93**
	Standard Deviation	0.072	0.054	0.051	0.058	0.069	0.021	
Canada	Return	0.034	0.034	0.021	0.022	0.027	0.007	0.79
	Standard Deviation	0.106	0.088	0.072	0.074	0.062	0.111	
Hong Kong	Return	0.018	0.017	0.013	0.008	0.013	0.006	1.56
	Standard Deviation	0.102	0.084	0.080	0.085	0.108	0.044	
Malaysia	Return	0.014	0.012	0.014	0.010	0.013	0.001	0.51
	Standard Deviation	0.112	0.103	0.113	0.104	0.116	0.032	
Thailand	Return	0.021	0.015	0.015	0.015	0.008	0.013	**2.85**
	Standard Deviation	0.090	0.084	0.078	0.078	0.096	0.055	
Singapore	Return	0.017	0.013	0.011	0.015	0.014	0.003	0.88
	Standard Deviation	0.102	0.085	0.088	0.093	0.097	0.044	
Australia	Return	0.016	0.017	0.017	0.017	0.014	0.002	0.72
	Standard Deviation	0.055	0.044	0.047	0.051	0.054	0.035	
New Zealand	Return	0.013	0.020	0.013	0.014	0.012	0.001	0.29
	Standard Deviation	0.055	0.053	0.055	0.051	0.058	0.049	
UK	Return	0.017	0.014	0.014	0.012	0.011	0.006	**3.10**
	Standard Deviation	0.052	0.043	0.042	0.041	0.048	0.024	
Ireland	Return	0.024	0.017	0.018	0.021	0.018	0.006	0.92
	Standard Deviation	0.084	0.072	0.059	0.071	0.065	0.086	
India	Return	0.029	0.032	0.028	0.034	0.028	0.001	0.37
	Standard Deviation	0.094	0.094	0.092	0.097	0.091	0.038	
Germany	Return	0.016	0.013	0.013	0.011	0.010	0.006	**2.33**
	Standard Deviation	0.052	0.041	0.043	0.047	0.054	0.030	
Austria	Return	0.013	0.016	0.011	0.014	0.014	-0.001	-0.16
	Standard Deviation	0.046	0.058	0.043	0.051	0.055	0.056	
Switzerland	Return	0.017	0.014	0.017	0.014	0.009	0.008	**2.99**
	Standard Deviation	0.057	0.047	0.043	0.046	0.055	0.032	
Japan	Return	0.010	0.007	0.007	0.005	0.007	0.003	**2.40**
	Standard Deviation	0.061	0.056	0.056	0.057	0.066	0.016	
South Korea	Return	0.014	0.021	0.018	0.013	0.009	0.005	1.17
	Standard Deviation	0.108	0.109	0.103	0.108	0.118	0.052	
Taiwan	Return	0.017	0.018	0.019	0.018	0.019	-0.002	-0.48
	Standard Deviation	0.094	0.091	0.092	0.087	0.089	0.052	
France	Return	0.022	0.017	0.018	0.017	0.015	0.007	**2.80**
	Standard Deviation	0.055	0.048	0.049	0.050	0.055	0.029	
Italy	Return	0.016	0.012	0.007	0.009	0.010	0.006	1.50
	Standard Deviation	0.071	0.061	0.059	0.066	0.069	0.049	
Greece	Return	0.031	0.028	0.033	0.029	0.037	-0.006	-0.76
	Standard Deviation	0.126	0.113	0.123	0.128	0.151	0.090	
Indonesia	Return	0.029	0.035	0.032	0.031	0.042	-0.014	*-1.82*
	Standard Deviation	0.122	0.128	0.126	0.118	0.118	0.092	
Spain	Return	0.028	0.030	0.025	0.019	0.027	0.001	0.22
	Standard Deviation	0.069	0.065	0.062	0.054	0.064	0.061	
Netherlands	Return	0.018	0.021	0.029	0.009	0.012	0.006	0.87
	Standard Deviation	0.071	0.073	0.084	0.064	0.070	0.089	
Belgium	Return	0.018	0.019	0.020	0.017	0.015	0.002	0.62
	Standard Deviation	0.064	0.058	0.058	0.058	0.061	0.049	
Portugal	Return	0.018	0.014	0.011	0.019	0.015	0.002	0.47
	Standard Deviation	0.057	0.055	0.057	0.058	0.065	0.064	
Sweden	Return	0.025	0.021	0.023	0.022	0.021	0.005	1.25
	Standard Deviation	0.077	0.064	0.069	0.065	0.073	0.046	
Norway	Return	0.027	0.024	0.017	0.020	0.024	0.003	0.60
	Standard Deviation	0.097	0.074	0.060	0.076	0.079	0.064	
Denmark	Return	0.020	0.015	0.018	0.017	0.012	0.008	**2.26**
	Standard Deviation	0.051	0.046	0.041	0.051	0.050	0.044	
Finland	Return	0.026	0.020	0.016	0.019	0.026	0.000	0.02
	Standard Deviation	0.073	0.059	0.055	0.057	0.086	0.063	

Next, we report the descriptive statistics of accrual-based quintile portfolios by country. Tables 2.5 to 2.7 give the arithmetic means of the earnings components and two risk proxies, beta and log-size. Consistent with prior studies, we find a negative relation between accruals and cash flows in all countries and a positive relation between accruals and earnings. We compute the betas of the countries' quintile portfolios according to the classical regression

$$R_{it} - R_{Ft} = \alpha_i + \beta_i(R_{Mt} - R_{Ft}) + \varepsilon_{it}, \qquad (2.2)$$

where R_{it} denotes the gross return of quintile i, R_{Ft} is the risk-free rate, and R_{Mt} is the market return of the country under examination. The extreme quintile portfolios exhibit high betas for two thirds of the countries, while the remaining portfolios appear to be homogeneous in terms of beta. Also, there is a size bias for the two extreme quintile portfolios. When we examine size measured in terms of total assets, we find that the two extreme portfolios are mostly populated by smaller companies in 26 out of 29 countries.

2.3.2 Fama-French Momentum Regressions

If we solely examine absolute returns of the hedge strategies, we might draw some false conclusions on the accrual strategies. Since some strategies show high volatility, the risk-adjusted performance may not be that convincing. Hence, we check whether the long-short portfolio returns can be attributed to common risk factors. We adopt the standard approach of Fama and French (1993), which we extend by an additional momentum factor, hence, we estimate the regression equation

$$R_{Lt} - R_{Ht} = \alpha + \beta(R_{Mt} - R_{Ft}) + \gamma R_{SMBt} + \delta R_{HMLt} + \eta R_{WMLt} + \varepsilon_t, \qquad (2.3)$$

where $R_{Lt} - R_{Ht}$ is the return difference of the lowest accruals quintile and the highest accruals quintile. For each country we compute country-specific factors as follows: A country's broad market index represents its market return R_{Mt}. A small cap index minus the risk-free rate, $R_{SCt} - R_{Ft}$, mimics the size factor R_{SMBt}. The value factor R_{HMLt} is the difference between a value index and the corresponding growth index, $R_{Vt} - R_{Gt}$. We compute the momentum-factor using a standard approach, i.e., each month we rank a country's stocks according to their previous 12-month performance. The returns to the momentum factor, R_{WMLt}, are then given by the returns of a strategy that is long in the winner quintile and short in the loser quintile of each month.

Table 2.5: Descriptive Statistics of Accruals Quintile Portfolios 1/3

The table gives mean values of the earnings components as well as two risk proxies, beta and log-size, over the whole period. Quintile portfolios are built yearly dependent on the level of accruals. In particular, *accruals* are computed as given in equation 2.1, *earnings* are approximated by operating income and *cash flows* are the difference between the two. All three components are standardized by the companies' total assets. As for risk proxies we consider the quintile portfolios' betas (arising from a standard CAPM) and size being measured as the average of log(total assets). The last column contains the difference between the extreme quintile portfolios' mean accruals figures.

		Portfolio Accrual Ranking					
Country		Lowest	2	3	4	Highest	Spread Hi-Lo
Panel A: Common Law Countries							
	Accruals	-0.176	-0.072	-0.039	-0.007	0.081	
	Cash Flows	0.101	0.112	0.089	0.052	-0.034	
USA	Earnings	-0.075	0.040	0.049	0.045	0.047	0.257
	Beta	1.442	1.083	1.030	1.166	1.393	
	Size	12.062	12.914	13.083	12.639	11.933	
	Accruals	-0.185	-0.078	-0.042	-0.010	0.077	
	Cash Flows	0.144	0.110	0.079	0.023	-0.063	
Canada	Earnings	-0.041	0.032	0.037	0.014	0.014	0.262
	Beta	0.777	0.562	0.495	0.594	0.540	
	Size	12.145	12.869	12.938	12.282	11.741	
	Accruals	-0.200	-0.061	-0.020	0.016	0.132	
	Cash Flows	0.140	0.106	0.060	0.033	-0.081	
Hong Kong	Earnings	-0.060	0.045	0.040	0.049	0.050	0.332
	Beta	1.075	0.880	0.828	0.887	1.132	
	Size	13.631	14.375	14.748	14.611	13.777	
	Accruals	-0.158	-0.050	-0.014	0.019	0.117	
	Cash Flows	0.187	0.109	0.068	0.043	-0.044	
Malaysia	Earnings	0.029	0.059	0.053	0.061	0.073	0.275
	Beta	0.921	0.842	0.925	0.856	0.964	
	Size	12.889	13.346	13.299	13.171	12.952	
	Accruals	-0.188	-0.078	-0.042	-0.004	0.112	
	Cash Flows	0.214	0.140	0.111	0.069	-0.053	
Thailand	Earnings	0.026	0.062	0.069	0.065	0.059	0.300
	Beta	1.010	0.954	0.865	0.862	1.065	
	Size	14.974	15.241	15.273	15.279	15.170	
	Accruals	-0.162	-0.059	-0.025	0.010	0.116	
	Cash Flows	0.158	0.114	0.075	0.044	-0.041	
Singapore	Earnings	-0.004	0.055	0.051	0.053	0.075	0.278
	Beta	1.048	0.878	0.910	0.949	0.987	
	Size	12.359	12.879	12.978	12.716	12.456	
	Accruals	-0.209	-0.073	-0.035	-0.004	0.106	
	Cash Flows	0.121	0.085	0.036	-0.006	-0.128	
Australia	Earnings	-0.089	0.012	0.001	-0.009	-0.023	0.315
	Beta	0.870	0.627	0.683	0.745	0.830	
	Size	11.583	12.430	12.149	11.663	11.424	
	Accruals	-0.157	-0.065	-0.030	-0.003	0.084	
	Cash Flows	0.250	0.172	0.111	0.098	0.011	
New Zealand	Earnings	0.093	0.107	0.080	0.095	0.096	0.241
	Beta	1.105	0.978	1.137	0.884	1.136	
	Size	12.208	13.006	12.920	12.523	12.010	
	Accruals	-0.185	-0.074	-0.039	-0.007	0.091	
	Cash Flows	0.142	0.129	0.097	0.057	-0.054	
UK	Earnings	-0.043	0.055	0.058	0.050	0.037	0.276
	Beta	1.156	0.922	0.901	0.872	1.048	
	Size	10.811	11.783	12.021	11.585	10.756	
	Accruals	-0.142	-0.053	-0.027	-0.002	0.064	
	Cash Flows	0.131	0.120	0.092	0.055	-0.023	
Ireland	Earnings	-0.011	0.067	0.065	0.052	0.042	0.206
	Beta	1.187	1.183	0.857	1.085	1.068	
	Size	11.550	12.803	12.785	12.225	11.317	
	Accruals	-0.144	-0.053	-0.017	0.018	0.102	
	Cash Flows	0.219	0.144	0.113	0.081	0.005	
India	Earnings	0.075	0.091	0.096	0.099	0.108	0.246
	Beta	0.873	0.855	0.869	0.920	0.865	
	Size	15.616	16.029	15.889	15.672	15.560	

Table 2.6: Descriptive Statistics of Accruals Quintile Portfolios 2/3

The table gives mean values of the earnings components as well as two risk proxies, beta and log-size, over the whole period. Quintile portfolios are built yearly dependent on the level of accruals. In particular, *accruals* are computed as given in equation 2.1, *earnings* are approximated by operating income and *cash flows* are the difference between the two. All three components are standardized by the companies' total assets. As for risk proxies we consider the quintile portfolios' betas (arising from a standard CAPM) and size being measured as the average of log(total assets). The last column contains the difference between the extreme quintile portfolios' mean accruals figures.

		Portfolio Accrual Ranking					
Country		Lowest	2	3	4	Highest	Spread Hi-Lo
Panel B: Code Law Countries							
	Accruals	-0.226	-0.095	-0.050	-0.009	0.105	
	Cash Flows	0.161	0.112	0.081	0.034	-0.074	
Germany	Earnings	-0.065	0.018	0.031	0.026	0.031	0.331
	Beta	1.067	0.829	0.898	0.991	1.163	
	Size	11.747	12.557	12.696	12.493	11.704	
	Accruals	-0.163	-0.081	-0.049	-0.018	0.064	
	Cash Flows	0.174	0.105	0.089	0.045	-0.024	
Austria	Earnings	0.011	0.024	0.040	0.027	0.040	0.227
	Beta	1.103	1.522	1.047	1.321	1.442	
	Size	12.754	12.857	13.215	12.902	12.352	
	Accruals	-0.150	-0.067	-0.041	-0.018	0.044	
	Cash Flows	0.164	0.118	0.101	0.070	0.013	
Switzerland	Earnings	0.014	0.051	0.060	0.052	0.057	0.194
	Beta	1.314	1.041	0.951	1.035	1.254	
	Size	13.039	13.666	13.555	13.591	13.062	
	Accruals	-0.101	-0.049	-0.029	-0.009	0.045	
	Cash Flows	0.139	0.092	0.074	0.054	0.005	
Japan	Earnings	0.038	0.043	0.044	0.045	0.050	0.146
	Beta	1.018	0.937	0.935	0.952	1.109	
	Size	17.901	18.141	18.008	17.841	17.517	
	Accruals	-0.171	-0.068	-0.030	0.009	0.108	
	Cash Flows	0.195	0.124	0.089	0.051	-0.046	
South Korea	Earnings	0.024	0.057	0.059	0.060	0.062	0.279
	Beta	0.811	0.743	0.719	0.721	0.821	
	Size	19.568	19.891	19.822	19.603	19.345	
	Accruals	-0.128	-0.053	-0.024	0.006	0.088	
	Cash Flows	0.163	0.102	0.073	0.051	-0.021	
Taiwan	Earnings	0.035	0.049	0.049	0.056	0.068	0.216
	Beta	1.039	1.016	1.027	0.971	0.977	
	Size	16.140	16.173	16.119	16.063	15.982	
	Accruals	-0.175	-0.074	-0.041	-0.012	0.069	
	Cash Flows	0.182	0.123	0.098	0.073	-0.002	
France	Earnings	0.007	0.049	0.056	0.061	0.068	0.244
	Beta	1.224	1.046	1.014	1.129	1.248	
	Size	12.039	12.963	13.300	12.828	11.802	
	Accruals	-0.156	-0.069	-0.041	-0.010	0.065	
	Cash Flows	0.150	0.102	0.083	0.046	-0.037	
Italy	Earnings	-0.007	0.033	0.042	0.036	0.029	0.221
	Beta	1.130	0.984	0.964	1.082	1.062	
	Size	12.979	13.339	13.397	13.231	12.586	
	Accruals	-0.176	-0.054	-0.010	0.041	0.154	
	Cash Flows	0.224	0.125	0.073	0.026	-0.087	
Greece	Earnings	0.048	0.071	0.064	0.067	0.067	0.330
	Beta	0.968	0.883	0.966	1.018	1.149	
	Size	11.304	11.609	11.479	11.235	11.130	
	Accruals	-0.182	-0.067	-0.026	0.014	0.133	
	Cash Flows	0.228	0.149	0.111	0.080	-0.031	
Indonesia	Earnings	0.046	0.082	0.085	0.094	0.102	0.315
	Beta	1.058	1.114	1.082	1.006	0.903	
	Size	20.464	21.020	20.925	20.715	20.523	

Table 2.7: Descriptive Statistics of Accruals Quintile Portfolios 3/3

Quintile portfolios are built yearly dependent on the level of accruals. The table gives mean values of the earnings components as well as two risk proxies, beta and log-size, over the whole period. In particular, *accruals* are computed as given in equation 2.1, *earnings* are approximated by operating income and *cash flows* are the difference between the two. All three components are standardized by the companies' total assets. As for risk proxies we consider the quintile portfolios' betas (arising from a standard CAPM) and size being measured as the average of log(total assets). The last column contains the difference between the extreme quintile portfolios' mean accruals figures.

		Portfolio Accrual Ranking					
Country		Lowest	2	3	4	Highest	Spread Hi-Lo
Panel B: Code Law Countries (continued)							
	Accruals	-0.144	-0.069	-0.042	-0.012	0.073	
	Cash Flows	0.191	0.132	0.099	0.071	-0.016	
Spain	Earnings	0.047	0.063	0.057	0.059	0.057	0.217
	Beta	1.198	0.967	1.025	0.947	1.114	
	Size	13.047	13.677	13.678	13.381	12.730	
	Accruals	-0.159	-0.078	-0.047	-0.014	0.055	
	Cash Flows	0.171	0.126	0.074	0.046	-0.030	
Portugal	Earnings	0.012	0.048	0.028	0.031	0.025	0.214
	Beta	1.181	1.149	1.320	1.105	0.748	
	Size	12.600	13.212	13.178	12.832	12.450	
	Accruals	-0.194	-0.083	-0.046	-0.012	0.079	
	Cash Flows	0.204	0.164	0.134	0.105	0.024	
Netherlands	Earnings	0.010	0.081	0.088	0.093	0.103	0.273
	Beta	1.180	1.062	1.070	1.058	1.119	
	Size	12.081	13.361	13.308	12.787	12.173	
	Accruals	-0.155	-0.082	-0.053	-0.021	0.064	
	Cash Flows	0.184	0.127	0.094	0.070	-0.010	
Belgium	Earnings	0.030	0.045	0.041	0.049	0.054	0.219
	Beta	1.554	1.287	1.134	1.182	1.387	
	Size	12.465	12.935	13.144	12.624	11.821	
	Accruals	-0.167	-0.068	-0.036	-0.007	0.072	
	Cash Flows	0.101	0.106	0.082	0.050	-0.038	
Sweden	Earnings	-0.066	0.038	0.046	0.044	0.034	0.239
	Beta	1.022	0.778	0.841	0.805	0.977	
	Size	13.467	14.453	14.793	14.201	13.564	
	Accruals	-0.191	-0.081	-0.045	-0.009	0.092	
	Cash Flows	0.122	0.091	0.079	0.054	-0.063	
Norway	Earnings	-0.069	0.010	0.035	0.045	0.030	0.283
	Beta	1.429	0.984	0.847	1.105	1.221	
	Size	13.494	14.320	14.523	14.159	13.230	
	Accruals	-0.157	-0.070	-0.038	-0.006	0.087	
	Cash Flows	0.170	0.115	0.080	0.058	-0.038	
Denmark	Earnings	0.013	0.046	0.042	0.051	0.049	0.244
	Beta	1.222	1.060	0.978	1.199	1.217	
	Size	13.848	14.247	14.235	14.093	13.724	
	Accruals	-0.159	-0.082	-0.052	-0.024	0.052	
	Cash Flows	0.185	0.144	0.116	0.106	0.026	
Finland	Earnings	0.025	0.062	0.064	0.082	0.077	0.211
	Beta	1.097	0.932	0.826	0.820	1.335	
	Size	11.802	12.589	12.678	12.672	11.942	

Summary	26 Countries in which both extreme accruals quintiles are smallest 19 Countries in which both extreme accruals quintiles exhibit the highest beta 18 Countries in which both extreme accruals quintiles are smallest and have highest beta 1 Country that does not exhibit any pattern related to size or beta

Given the factor structure in equation (2.3), we can identify the alpha generated by the accrual-based hedge strategy net of common risk factors. Across all countries unreported results convey that market and size factors capture the excess returns for the extreme quintile portfolios, thus confirming our descriptive analysis in the previous section.[2] Concerning the performance of the long-short strategies, Table 2.8 reveals that the model's explanatory power is generally low. The remaining positive alphas are significant at the 5% level for seven out of 29 countries, i.e., the U.S., Thailand, Germany, Switzerland, Japan, France, and Denmark. These countries have already shown significant return figures in Table 2.4. However, the U.K. drops out of the previous list indicating that the absolute return is not robust to common risk factors. We observe that the statistically significant hedge strategies are also promising in terms of economical significance, since their monthly alphas range from 31 (Japan) to 139 (Thailand) basis points. The latter is followed by 104 basis points for the U.S. which is consistent with prior results. When we relax the significance level to 10%, the South Korean hedge strategy gives a significant alpha of 76 basis points and the Swedish hedge strategy delivers 66 basis points.

By inspecting the legal tradition of the countries in which the accrual anomaly seems to hold, we detect the accrual anomaly at the 5% significance level for two out of 11 countries with a common law tradition and for five out of 18 countries with a code law tradition. Therefore, we are tempted to conclude that the accrual anomaly is more likely to occur in code law countries than in common law countries, contrasting the view of Pincus, Rajgopal, and Venkatachalam (2007), but supporting Leuz, Nanda, and Wysocki (2003) who argue that earnings management is less of a concern in common law countries due to high investor protection.

In Table 2.9, we summarize and compare our results with previous studies on the global accrual anomaly. In terms of risk-adjusted returns, our findings are closest to those of Pincus, Rajgopal, and Venkatachalam (2007) with a correlation of alphas equal to 0.64. As for the study of LaFond (2005) the alphas' correlation is 0.26. However, this figure rises to 0.61, when we exclude Canada and Denmark.

[2] These results can be obtained upon request.

Table 2.8: Fama-French-Momentum-Regressions of Hedge Portfolios

The table gives the results of a regression according to equation (2.3) using 154 monthly returns ranging from May 1994 to February 2007. Alphas significantly positive on a 10%-level are in italics and in bold face if significantly positive on a 5%-level. The corresponding t-statistics are below the coefficients.

Country		alpha α	Market β	Size γ	Value δ	Momentum η	Adj. R^2
USA	Coefficient	**0.0104**	0.0194	-0.0182	0.0591	-0.0367	1.53
	t-stat	5.9686	0.2830	-0.3382	1.0393	-1.9684	
Canada	Coefficient	0.0050	0.6064	-0.0778	0.3580	-0.2098	4.55
	t-stat	0.5653	1.3741	-0.2135	2.2206	-1.7606	
Hong Kong	Coefficient	0.0052	0.0259	-0.0707	-0.1018	0.0595	4.05
	t-stat	1.4792	0.3734	-1.1420	-1.4525	1.5404	
Malaysia	Coefficient	0.0009	0.1232	-0.1065	0.0491	0.0398	6.55
	t-stat	0.3615	2.6891	-2.9475	0.7077	1.2967	
Thailand	Coefficient	**0.0139**	-0.0550	0.0190	-0.1402	0.0113	4.60
	t-stat	3.1376	-0.7304	0.2309	-2.0404	0.2961	
Singapore	Coefficient	0.0027	-0.0373	0.0849	0.0156	0.0044	-0.82
	t-stat	0.7462	-0.4330	1.2172	0.1689	0.1031	
Australia	Coefficient	0.0020	0.1680	-0.0724	-0.1443	0.0824	4.37
	t-stat	0.7235	1.4215	-0.6982	-1.8310	2.0712	
New Zealand	Coefficient	0.0012	-0.0225	0.0326	-0.0199	-0.0540	-1.74
	t-stat	0.2866	-0.2124	0.3523	-0.2867	-1.1500	
UK	Coefficient	0.0026	0.0601	0.0909	-0.0102	0.1187	11.10
	t-stat	1.3255	0.9448	1.6958	-0.1571	3.8314	
Ireland	Coefficient	0.0041	-0.0633	0.1994	0.0124	0.1041	0.86
	t-stat	0.5733	-0.3014	1.0624	0.1171	1.8617	
India	Coefficient	0.0009	-0.0405	0.0378	-0.0273	-0.0222	-1.69
	t-stat	0.2924	-0.6576	0.8101	-0.5338	-0.7381	
Germany	Coefficient	**0.0061**	-0.0990	0.1008	0.0663	-0.0239	1.01
	t-stat	2.4057	-1.8301	1.2535	1.1615	-0.6936	
Austria	Coefficient	0.0007	0.1039	-0.1049	-0.1983	0.0338	1.23
	t-stat	0.1421	0.6712	-0.5600	-2.2071	0.6006	
Switzerland	Coefficient	**0.0078**	-0.0613	-0.0290	0.1698	0.0088	1.67
	t-stat	2.9289	-0.7611	-0.3731	2.5645	0.2675	
Japan	Coefficient	**0.0031**	0.1554	-0.1779	0.0200	0.0269	13.79
	t-stat	2.5275	3.0905	-4.0193	0.4814	1.4174	
South Korea	Coefficient	*0.0076*	-0.1103	0.0510	-0.2857	0.0454	8.84
	t-stat	1.9418	-1.6191	0.7231	-3.4277	0.9651	
Taiwan	Coefficient	-0.0025	0.2304	-0.1743	0.3598	-0.0673	10.66
	t-stat	-0.6129	2.3556	-1.9602	4.2221	-1.5851	
France	Coefficient	**0.0063**	0.0718	-0.0858	-0.0980	-0.0473	2.79
	t-stat	2.7136	1.1512	-1.2559	-1.9604	-1.3566	
Italy	Coefficient	0.0055	-0.3552	0.3461	-0.1665	-0.0390	4.65
	t-stat	1.3993	-2.9420	2.9700	-2.0162	-0.9123	
Greece	Coefficient	0.0026	0.0761	-0.2096	-0.0024	-0.3109	20.14
	t-stat	0.3774	0.5217	-1.8341	-0.0089	-5.4956	
Indonesia	Coefficient	-0.0146	0.0475	-0.1051	0.1587	-0.0431	0.19
	t-stat	-1.9324	0.5240	-1.3961	1.5784	-0.9275	
Spain	Coefficient	0.0017	0.1983	-0.1386	0.1037	-0.0810	1.10
	t-stat	0.3292	1.4736	-0.8436	0.8118	-1.6772	
Portugal	Coefficient	0.0018	0.4726	-0.0103	-0.0711	0.0133	6.04
	t-stat	0.2401	2.7464	-0.0632	-0.4061	0.2594	
Netherlands	Coefficient	0.0050	0.0073	0.0376	-0.1220	-0.0848	0.54
	t-stat	1.1871	0.0672	0.3034	-1.3904	-1.7659	
Belgium	Coefficient	0.0041	-0.0448	0.1483	-0.1250	-0.0571	-1.30
	t-stat	0.7365	-0.3077	0.8259	-0.8616	-0.8548	
Sweden	Coefficient	*0.0066*	0.0365	-0.0633	0.0253	-0.0870	1.75
	t-stat	1.7314	0.3098	-0.4671	0.3981	-2.5105	
Norway	Coefficient	0.0000	0.0252	0.1222	0.2116	0.0508	2.60
	t-stat	-0.0043	0.1444	0.7832	1.6838	1.1052	
Denmark	Coefficient	**0.0091**	-0.1891	0.0746	0.0402	-0.0229	1.17
	t-stat	2.3596	-1.7287	0.6198	0.5572	-0.4189	
Finland	Coefficient	-0.0009	-0.2980	0.1786	-0.1452	0.0523	4.29
	t-stat	-0.1714	-2.6480	1.1945	-1.8435	0.9364	

Table 2.9: Studies on the Global Accrual Anomaly

The table summarizes the findings on the global accrual anomaly of Pincus, Rajgopal, and Venkatachalam (2007), LaFond (2005), Liodakis, Brar, Gadaut, and Sharma (2004), and ours. Whereas Liodakis, Brar, Gadaut, and Sharma (2004) report average annual returns (see their Figure 7) all other studies provide alphas net of similar risk factors. We summarize Table 2.8 of our study, Table 6 of Pincus, Rajgopal, and Venkatachalam (2007), and Table 3 of LaFond (2005). Coefficients that are significant on a 10%-level are in italics, coefficients significant on a 5%-level or better appear in bold face. Yearly figures are given in percentage terms and monthly figures are given in basis points. GV denotes Global Vantage (Industrial/Commercial), Comp. is Compustat, DS is Datastream, and BSM stands for Balance Sheet Method. CGB-BMI denotes the Citigroup Bank Broad Market Indexes.

Panel A: Data Characteristics

	Our Study	Pincus et al. (2007)	LaFond (2005)	Liodakis et al. (2004)
Balance Sheet Data	DS	GV	Comp.(USA)/DS	DS
Return Data	DS	GV Issues	CRSP (USA)/DS	DS
Period	1994–2007	1994–2002	1990–2003	1989–2004
Sample Size	132,493 FY	62,027 FY	130,188 FY	CGB-BMI
FY per year	10,192 FY	6,892 FY	9,299 FY	2,000 FY
Accruals Method	BSM	BSM	BSM	BSM

Panel B: Common Law Countries' Alphas

	Our Study yearly	Our Study monthly	Pincus et al. (2007) yearly	Pincus et al. (2007) monthly	LaFond (2005) yearly	LaFond (2005) monthly	Liodakis et al. (2004) yearly	Liodakis et al. (2004) monthly
US	**12.48**	**104**	**8.40**	**70**	**12**	**100**	10.6	88
Canada	6.00	50	**8.28**	**69**	**9**	**75**	-	-
Hong Kong	6.24	52	5.04	42	**17.04**	**142**	-	-
Malaysia	1.08	9	**8.64**	**72**	-	-	-	-
Thailand	**16.68**	**139**	**20.64**	**172**	-	-	-	-
Singapore	3.24	27	-1.44	-12	**8.28**	**69**	-	-
Australia	2.40	20	**17.88**	**149**	**12.12**	**101**	-	-
New Zealand	1.44	12	-	-	-	-	-	-
UK	3.12	26	**9.96**	**83**	**9.96**	**83**	5.13	43
Ireland	4.92	41	-	-	-	-	9.09	76
India	1.08	9	4.70	39	-	-	9.09	76

Panel C: Code Law Countries' Alphas

	Our Study yearly	Our Study monthly	Pincus et al. (2007) yearly	Pincus et al. (2007) monthly	LaFond (2005) yearly	LaFond (2005) monthly	Liodakis et al. (2004) yearly	Liodakis et al. (2004) monthly
Germany	**7.32**	**61**	*6.60*	*55*	*3.84*	*32*	9.11	76
Austria	0.84	7	-	-	-	-	-	-
Switzerland	**9.36**	**78**	4.92	41	**9.6**	**80**	8.38	70
Japan	**3.72**	**31**	**5.76**	**48**	**3.84**	**32**	4.2	35
South Korea	*9.12*	*76*	-	-	-	-	-	-
Taiwan	-3.00	-25	-0.48	-4	-	-	-	-
France	**7.56**	**63**	*8.16*	*68*	**10.92**	**91**	3.28	27
Italy	6.00	55	*11.76*	*98*	**10.44**	**87**	3.82	32
Greece	3.12	26	-	-	-	-	-	-
Indonesia	**-17.52**	**-146**	-12.60	-105	-	-	-	-
Spain	2.04	17	-6.96	-58	**11.52**	**96**	0.29	2
Portugal	2.16	18	-	-	-	-	-	-
Netherlands	6.00	50	2.16	18	**7.08**	**59**	13.38	112
Belgium	4.92	41	-	-	**8.88**	**74**	-	-
Sweden	*7.92*	*66*	9.24	77	*8.28*	*69*	6.36	53
Norway	0.00	0	-	-	2.76	23	-0.71	-6
Denmark	**10.92**	**91**	*8.52*	*71*	-0.96	-8	4.3	36
Finland	-1.08	-9	-	-	-	-	-	-

	Our Study	Pincus et al. (2007)	LaFond (2005)	Liodakis et al. (2004)
Σ at 5%	7/29	7/20	13/17	NA
Σ at 10%	9/29	10/20	15/17	NA

Chapter 3

Data Snooping Biases and Market Anomalies

From the previous chapter, we learn that out of 29 countries, seven or nine exhibit positive and significant alphas, depending on the degree of significance enforced. This result already casts doubt on the existence of the accrual anomaly in most of the countries. Nevertheless, we hesitate to claim that we can safely abandon the notion of the accrual anomaly as being a global phenomenon and that the anomaly more likely emerges in code law countries because the detected alphas may be spurious in the absence of multiple testing controls.

3.1 Accounting for Multiple Testing

In examining a market anomaly as a global phenomenon, we test for it in a large number of equity markets. Hence, we are in the general set-up of testing several hypotheses at once and must apply appropriate multiple testing procedures. These testing procedures either control for the *familywise error rate* (FWE) or the *false discovery proportion* (FDP). Below, we will briefly introduce the concept behind these methods.

3.1.1 Methods Based on the Familywise Error Rate (FWE)

The traditional way to account for multiple testing is to control the familywise error rate (FWE), defined as the probability of rejecting at least one of the true null hypotheses. If this objective is achieved, one can be confident that all hypotheses that have been rejected are indeed false (instead of some true ones having been rejected by chance alone). Many methods that control the FWE exist, the simplest one being the well-known Bonferroni (1936) method, which consists of a plain p-value adjustment, i.e., the initial significance level α is divided by the number of hypotheses under test. Evidently, this method is strict and would result in an outright rejection of any given market anomaly. However, it is also important to use a method that provides as much power as possible so that false hypotheses have a chance of being detected.

In our set-up, we would like to detect as many countries as possible where the anomaly actually exists. In this respect, the recent proposal of Romano and Wolf (2005) appears to be the state of the art. On the one hand, it improves upon Bonferroni-type methods based on the individual p-values by incorporating the dependence structure across test statistics. On the other hand, it improves on the bootstrap reality check of White (2000) by incorporating a stepwise approach and by employing studentized test statistics.

For our case, the most suitable method is the so-called k-StepM method, which we will briefly discuss in the following. Consider S individual decision problems of the form

$$H_s : \theta_s \leq 0 \text{ versus } H_s^{'} : \theta_s > 0, \quad 1 \leq s \leq S, \tag{3.1}$$

each referring to the hedge strategy in country s. We define the parameter θ_s in such a way that under the null hypothesis H_s, strategy s does not beat the zero benchmark. Given the time series of the hedge strategies, we can compute the test statistic $w_{T,s}$ with an estimate of its standard deviation $\hat{\sigma}_{T,s}$ based on the returns and the strategies' alphas according to the Fama-French momentum regressions. In particular, using monthly hedge returns $x_{t,s}$, we compute average monthly buy-and-hold returns as in Section 6.2. Thus, we have

$$w_{T,s} = \bar{x}_{T,s} = \frac{1}{T}\sum_{t=1}^{T} x_{t,s}. \tag{3.2}$$

To account for potential serial correlation in the return series, the studentization of test statistics is pursued using a kernel variance estimator based on the Parzen kernel, see Andrews (1991). Likewise, the test statistic for the alpha is the intercept from estimating equation (2.3),

$$w_{T,s} = \hat{\alpha}_{T,s}, \tag{3.3}$$

studentized by the estimated standard deviation of $\hat{\alpha}_{T,s}$, again using the Parzen kernel.

Within the k-StepM method, we first re-label strategies such that r_1 corresponds to the largest test statistic and r_S to the smallest one. Then, we need to determine a confidence region of the form

$$[w_{T,r_1} - \sigma_{T,r_1} d_1, \infty) \times \cdots \times [w_{T,r_S} - \sigma_{T,r_S} d_1, \infty). \tag{3.4}$$

Whenever $0 \notin [w_{T,r_s} - \sigma_{T,r_s} d_1, \infty)$, we reject H_s for $s = 1, ..., S$. To control the FWE, d_1 ideally is given by the $(1-\alpha)$-quantile of the distribution of the largest 'centered' studentized[1] statistic

$$\frac{w_{T,s} - \theta_s}{\sigma_{T,s}}$$

among all true hypotheses. However, we do not know which hypotheses are true and we do not know the true probability mechanism P. Therefore, we take the largest difference among all hypotheses and we replace P by a bootstrap estimate $\hat{P}$, which implies that the StepM method will only allow for asymptotic control of the FWE. This feature is shared by all other commonly used multiple testing procedures.

If we suppose that we have rejected $R_1 < k$ hypotheses, we can construct a new confidence region to reexamine the remaining $(S - R_1)$ smallest test statistics

$$[w_{T,R_1+1} - \sigma_{T,R_1+1} d_2, \infty) \times \cdots \times [w_{T,r_S} - \sigma_{T,r_S} d_2, \infty), \tag{3.5}$$

which is a smaller confidence region, because it typically holds that $d_1 > d_2 > \cdots > d_S$. Hence, we can reject more false hypotheses. Therefore, such a stepwise procedure is more powerful than the single-step method. For the computation of d_2, we again lack both P and the set of true hypotheses. For P, we use the bootstrap estimate $\hat{P}$. However, we now only maximize over the set of hypotheses that have not been rejected yet. Since this is a smaller set, $S - R_1$ versus S elements, d_2 will typically be smaller than d_1 (and at most equally large). If no additional rejection occurs, we stop. Otherwise, we proceed in the same fashion until there are no further rejections.

3.1.2 Method Based on the False Discovery Proportion (FDP)

When the number of hypotheses under test is very large, the error control may be based on the false discovery proportion rather than on the familywise error rate. Let F be the number of false rejections arising from a multiple testing method and let R be the total number of rejections. We define the FDP as the fraction F/R,

[1] Studentization requires that the average return be divided by its standard error. To obtain valid confidence intervals for the expected return, we must multiply these quantiles with the country's return standard error. Romano and Wolf (2005) advocate the use of studentization, since it is more powerful and gives more appropriate coverage probabilities for individual θ_{r_s}, especially when test statistics show different standard deviations. Clearly, the latter applies to our case.

given that $R > 0$. Otherwise, the FDP is zero. A multiple testing method controls the FDP at level α if $P(FDP > \gamma) \leq \alpha$, for any P, at least asymptotically. Typical values of γ are 0.05 and 0.1.

Romano, Shaikh, and Wolf (2008) present a generalized version of the StepM method that allows for controlling the FDP, the FDP-StepM$_\gamma$ method. The method is somewhat complex and the reader is referred to the paper for the details. However, the first step of the method is easy to understand and works as follows. Consider controlling the FDP with $\gamma = 0.1$. The method starts out by applying the StepM method. If less than nine hypotheses are rejected, the method stops. If nine or more hypotheses are rejected, the method continues and some further hypotheses might be rejected subsequently.

3.2 Is the Global Accrual Anomaly Due to Data Snooping?

Reconciling the results of the traditional analysis, we are left with seven or nine positive and significant alphas out of 29 strategies, depending on the degree of significance enforced. Such a result could occur by chance alone, hence, we now account for multiple testing issues using the methods presented above. Clearly, it would be undue to lump together all 29 strategies since the respective countries differ in accounting measurement rules and institutional environments. Prior literature suggests that a country's legal tradition might serve as an appropriate separator. For instance, Pincus, Rajgopal, and Venkatachalam (2007) conjecture that the accrual anomaly is more likely to occur in common law countries since the respective accounting systems give managers more leeway in managing earnings through creative accruals accounting. Therefore, since the differentiation between code law and common law countries may have some significant economic implications, we perform the multiple hypotheses procedures on sub-samples grouped according to their legal tradition.

To control the FWE, we use the StepM method, i.e., $k = 1$ is the appropriate choice given the number of strategies under study. To control the FDP, we use the FDP-StepM$_\gamma$ method with $\gamma = 0.1$. We perform the multiple testing at a significance level of 5% and present results for the return of the hedge strategies as well as their alphas arising from the Fama-French momentum regressions. For the bootstrap method, we choose the stationary bootstrap with an average block size of 12 months.[2]

[2]Using the stationary bootstrap with an average block size of six months leaves results virtually unchanged.

Table 3.1: Multiple Testing: Code Law versus Common Law

The table gives the lower confidence band c_l for the returns and alphas as obtained by the StepM and FDP-StepM$_{0.1}$ method using studentized test statistics. Both StepM methods are applied considering common law and code law countries separately. The *rej*-columns contain the resulting decision where 1 indicates rejection of $\theta_s = 0$ (capital market efficiency). Panel A provides information on common law countries and Panel B covers code law countries.

	Returns					Alphas				
Country	Return	*StepM*		*FDP-StepM*$_{0.1}$		Alpha	*StepM*		*FDP-StepM*$_{0.1}$	
		c_l	rej	c_l	rej		c_l	rej	c_l	rej
Panel A: Common Law Countries										
USA	0.0101	0.0059	1	0.0059	1	0.0104	0.0049	1	0.0049	1
Canada	0.0070	-0.0150	0	-0.0150	0	0.0050	-0.0231	0	-0.0231	0
Hong Kong	0.0055	-0.0032	0	-0.0032	0	0.0052	-0.0059	0	-0.0059	0
Malaysia	0.0013	-0.0050	0	-0.0050	0	0.0009	-0.0071	0	-0.0071	0
Thailand	0.0127	0.0018	1	0.0018	1	0.0139	0.0001	1	0.0001	1
Singapore	0.0031	-0.0056	0	-0.0056	0	0.0027	-0.0087	0	-0.0087	0
Australia	0.0020	-0.0049	0	-0.0049	0	0.0020	-0.0068	0	-0.0068	0
New Zealand	0.0012	-0.0086	0	-0.0086	0	0.0012	-0.0116	0	-0.0116	0
UK	0.0059	0.0012	1	0.0012	1	0.0026	-0.0036	0	-0.0036	0
Ireland	0.0064	-0.0107	0	-0.0107	0	0.0041	-0.0183	0	-0.0183	0
India	0.0011	-0.0064	0	-0.0064	0	0.0009	-0.0089	0	-0.0089	0
Panel B: Code Law Countries										
Germany	0.0057	-0.0013	0	-0.0013	0	0.0061	-0.0010	0	-0.0010	0
Austria	-0.0007	-0.0137	0	-0.0137	0	0.0007	-0.0122	0	-0.0122	0
Switzerland	0.0076	0.0003	1	0.0003	1	0.0078	0.0004	1	0.0004	1
Japan	0.0032	-0.0006	0	-0.0006	0	0.0031	-0.0003	0	-0.0003	0
South Korea	0.0049	-0.0070	0	-0.0070	0	0.0076	-0.0033	0	-0.0033	0
Taiwan	-0.0020	-0.0141	0	-0.0141	0	-0.0025	-0.0136	0	-0.0136	0
France	0.0065	-0.0001	0	-0.0001	0	0.0063	-0.0002	0	-0.0002	0
Italy	0.0059	-0.0053	0	-0.0053	0	0.0055	-0.0055	0	-0.0055	0
Greece	-0.0055	-0.0262	0	-0.0262	0	0.0026	-0.0164	0	-0.0164	0
Indonesia	-0.0135	-0.0346	0	-0.0346	0	-0.0146	-0.0356	0	-0.0356	0
Spain	0.0011	-0.0129	0	-0.0129	0	0.0017	-0.0130	0	-0.0130	0
Portugal	0.0062	-0.0142	0	-0.0142	0	0.0018	-0.0186	0	-0.0186	0
Netherlands	0.0024	-0.0089	0	-0.0089	0	0.0050	-0.0067	0	-0.0067	0
Belgium	0.0024	-0.0123	0	-0.0123	0	0.0041	-0.0113	0	-0.0113	0
Sweden	0.0046	-0.0059	0	-0.0059	0	0.0066	-0.0041	0	-0.0041	0
Norway	0.0031	-0.0117	0	-0.0117	0	0.0000	-0.0148	0	-0.0148	0
Denmark	0.0080	-0.0021	0	-0.0021	0	0.0091	-0.0016	0	-0.0016	0
Finland	0.0001	-0.0144	0	-0.0144	0	-0.0009	-0.0157	0	-0.0157	0
Common Law Countries			3		3			2		2
Code Law Countries		Σ	1		1			1		1
All Countries			4		4			3		3

In Table 3.1, we report the results of the multiple testing procedures together with the countries' return statistics. Panel A of Table 3.1 provides information on common law countries and Panel B covers code law countries. We perform both the StepM and FDP-StepM$_{0.1}$ method on the countries' returns and Fama-French momentum alphas and provide the lower confidence band c_l for the monthly returns and alphas using studentized test statistics. Since we are in a one-sided test setting, we only report the lower limits of the confidence interval, as computed in the last step of the StepM and FDP-StepM$_{0.1}$ method, respectively. The value in the column labeled rej equals 1 if $0 \notin [c_l, \infty)$, which indicates the rejection of capital market efficiency and suggests the presence of an accrual anomaly in the respective country.

First, we focus on the results for the common law countries in Panel A. Among the 11 countries we obtain three rejections on behalf of the hedge strategy returns for the U.S., the U.K., and Thailand. Both the StepM and the FDP-StepM$_{0.1}$ method also reject the null for the U.S. and Thailand when replacing the test statistics by the strategies' alphas while the U.K. alpha does not appear to be robust. Note that, as pointed out in Section 3.1.2, controlling the FWE with the StepM method is in this case equivalent to control of the FDP by the FDP-StepM$_{0.1}$ method since the number of hypotheses rejected is less than nine.

Second, we inspect the results for the code law countries in Panel B. Among the 17 countries only Switzerland defies capital market efficiency since both, hedge return and alpha, are found to be robust with respect to data snooping. Thus, reconciling the obtained multiple testing results with the ones of the naïve approach we notice that the few anomalous pattern within the common law bucket are by and large robust whereas the original findings for the code law countries vanish when controlling for data snooping. Hence, our results essentially support the findings of Pincus, Rajgopal, and Venkatachalam (2007) who also find the phenomenon to be rather specific to common law countries.

3.3 Sensitivity Check: International Momentum Revisited

Given the striking results for the accrual anomaly, the question is whether multiple testing methods are 'too conservative', since there are only few rejections of capital market efficiency deemed to be robust. In other words, based on data sets of customary sample sizes, any asset pricing anomaly might have difficulty passing the employed multiple testing method. To address this reasonable objection, we check whether the momentum effect is robust to multiple testing. Given the extensive out-of-sample evidence from both temporal and geographic perspectives, researchers widely acknowledge the presence and robustness of abnormal momentum returns.[3] Thus, momentum strategies may serve as an adequate benchmark for heuristically validating the testing method we apply to the accrual anomaly. In contrast to the accrual anomaly we do not apply the multiple testing procedure to specific subsets but across all countries since the momentum phenomenon is only hinging on return

[3]For the U.S. markets see, e.g., Jegadeesh and Titman (1993) and (2001). For international studies see, e.g., Rouwenhorst (1998), Griffin, Ji, and Martin (2003) and (2005). Also, Schwert (2003) and Fama and French (2008) argue that momentum is among the few robust anomalies.

data and not on country-specific accounting data. Table 3.2 displays the multiple testing results for momentum returns and alphas, the latter arising from a standard Fama-French setting.

Table 3.2: Multiple Testing: Momentum

The table gives the lower confidence band c_l for the returns and alphas as obtained by the StepM and FDP-StepM$_{0.1}$ method using studentized test statistics. The *rej*-columns contain the resulting decision where 1 indicates rejection of $\theta_s = 0$ (capital market efficiency). Panel A provides information on common law countries and Panel B covers code law countries.

	Returns					Alphas				
Country	Return	*StepM*		*FDP-StepM$_{0.1}$*		Alpha	*StepM*		*FDP-StepM$_{0.1}$*	
		c_l	rej	c_l	rej		c_l	rej	c_l	rej
Panel A: Common Law Countries										
USA	0.0132	0.0023	1	0.0045	1	0.0280	0.0101	1	0.0168	1
Canada	0.0100	-0.0024	0	0.0002	1	0.0159	0.0061	1	0.0098	1
Hong Kong	0.0071	-0.0106	0	-0.0070	0	0.0097	-0.0020	0	0.0024	1
Malaysia	0.0038	-0.0123	0	-0.0090	0	0.0080	-0.0009	0	0.0024	1
Thailand	0.0063	-0.0155	0	-0.0111	0	0.0069	-0.0062	0	-0.0013	0
Singapore	0.0075	-0.0085	0	-0.0052	0	0.0126	0.0043	1	0.0074	1
Australia	0.0064	-0.0043	0	-0.0021	0	0.0089	0.0004	1	0.0036	1
New Zealand	0.0099	-0.0005	0	0.0016	1	0.0101	0.0020	1	0.0050	1
UK	0.0141	0.0010	1	0.0037	1	0.0154	0.0050	1	0.0089	1
Ireland	0.0097	-0.0046	0	-0.0017	0	0.0145	0.0047	1	0.0084	1
India	0.0145	-0.0007	0	0.0024	1	0.0182	0.0068	1	0.0111	1
Panel B: Code Law Countries										
Germany	0.0160	0.0051	1	0.0073	1	0.0200	0.0121	1	0.0151	1
Austria	0.0051	-0.0032	0	-0.0015	0	0.0047	-0.0014	0	0.0009	1
Switzerland	0.0149	0.0013	1	0.0041	1	0.0175	0.0064	1	0.0106	1
Japan	0.0019	-0.0090	0	-0.0068	0	0.0056	-0.0012	0	0.0014	1
South Korea	0.0028	-0.0201	0	-0.0154	0	0.0107	-0.0033	0	0.0020	1
Taiwan	0.0009	-0.0172	0	-0.0135	0	-0.0002	-0.0134	0	-0.0084	0
France	0.0121	0.0004	1	0.0028	1	0.0138	0.0046	1	0.0081	1
Italy	0.0110	-0.0027	0	0.0001	1	0.0139	0.0047	1	0.0081	1
Greece	0.0162	-0.0008	0	0.0027	1	0.0186	0.0088	1	0.0125	1
Indonesia	-0.0021	-0.0237	0	-0.0193	0	0.0034	-0.0119	0	-0.0061	0
Spain	0.0123	0.0011	1	0.0034	1	0.0108	0.0024	1	0.0056	1
Portugal	0.0078	-0.0082	0	-0.0050	0	0.0104	-0.0032	0	0.0019	1
Netherlands	0.0208	0.0036	1	0.0071	1	0.0268	0.0170	1	0.0207	1
Belgium	0.0147	0.0036	1	0.0059	1	0.0185	0.0107	1	0.0137	1
Sweden	0.0215	0.0060	1	0.0091	1	0.0283	0.0171	1	0.0214	1
Norway	0.0208	0.0059	1	0.0089	1	0.0244	0.0147	1	0.0183	1
Denmark	0.0118	0.0039	1	0.0055	1	0.0149	0.0091	1	0.0112	1
Finland	0.0186	0.0060	1	0.0085	1	0.0220	0.0117	1	0.0155	1
Common Law Countries			2		5			8		10
Code Law Countries		Σ	10		12			12		16
All Countries			12		17			20		26

As for the returns, the StepM gives 12 rejections among the set of 17 naïve abnormal momentum returns as documented in Table 2.3. Notably, all of these 17 candidates are detected by the FDP-StepM$_{0.1}$. As for the alphas, we even obtain 20 rejections judging by the StepM method and 26 rejections judging by the FDP-StepM$_{0.1}$ method. For most Asian countries, the multiple testing methods provide no statistical evidence for a momentum anomaly. This result supports the findings of Griffin, Ji, and Martin (2003, 2005) that the momentum anomaly is less pronounced in Asian countries. However, they do not account for multiple hypotheses testing. Nevertheless, given this large number of rejections, the previous evidence on momentum in international equity markets is reinforced. Since increasing amounts of capital have recently sought to exploit this phenomenon, this evidence warrants further investigation, which we provide in Chapter 5.

Chapter 4

The Demise of the Accrual Anomaly

It is puzzling why the accrual anomaly is confined to few markets. There might be several plausible explanations worth of consideration. First, to be misled by accruals-related earnings management, investors of a given country need to fixate on top-down earnings. Thus, countries in which earnings are less relevant to stock prices are less likely to exhibit anomalous patterns with respect to accruals. In fact, some studies[1] argue that value relevance of earnings is more pronounced in market-oriented financial systems as opposed to bank-oriented ones. However, as documented by Land and Lang (2002), the globalization of firms has led to a convergence in accounting practices, which will most likely translate to convergence in value relevance of earnings as well.

Second, Teoh, Welch, and Wong (1998a, 1998b) provide evidence that intensive accruals accounting is used for window dressing in U.S. public equity offerings. Given that the U.S. accounts for the largest stake in worldwide equity issuances (Kim and Weisbach, 2008), it may be that managers of non-U.S. companies are more likely to refrain from manipulating earnings, because they lack the incentive of an equity issuance. Still, non-U.S. companies may nonetheless exhibit earnings smoothing prior to a given equity issuance. However, since this pattern will be confined to a small subsample, we fail to find sufficient support for a broad market anomaly with respect to accruals. This argument may also rationalize the observation of the British accrual anomaly since the U.K. ranks first among the European countries in terms of equity issuances.

Third, if earnings fixation is mostly uniform across countries, it is straightforward to speculate about significant differences in the decomposition of earnings into cash flows and accruals. Financial reporting standards in common law countries may

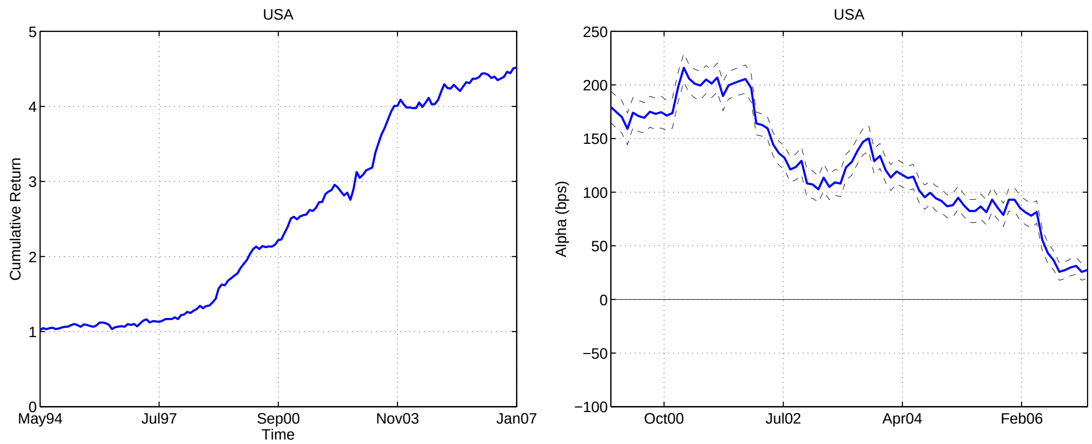
[1] See, e.g., Alford, Jones, Leftwich, and Zmijewski (1993) and Ali and Hwang (2000).

allow for a more discretionary use of accruals as compared to other countries. While we have documented earlier that the level of accruals (measured as a fraction of total assets) is on average fairly similar across countries, a given business transaction may more easily be used for earnings smoothing under U.S. accounting standards. While this characteristic may give rise to more accounting manipulations in the U.S and other common law countries, there is also an antagonistic force at work inherent in the U.S. capital market. In particular, Leuz, Nanda, and Wysocki (2003) provide evidence that earnings management is less of a concern in common law countries due to high investor protection. Accordingly, Graham, Harvey, and Rajgopal (2005, 2006) observe that if U.S. companies play the earnings game, they primarily do so through "real earnings management", such as deferring a valuable project or slashing R&D expenditures, and to a much lesser extent through clever accrual accounting.

Irrespective of the sources to the abnormal returns in these markets, mispricing or chance, investors will most likely try to benefit from implementing related trading strategies, causing the anomaly to weaken or even disappear. While research published shortly after the initial study of Sloan (1996) suggests that institutional investors do not act on information from accruals (Ali, Hwang, and Trombley, 2000; Bradshaw and Sloan, 2001), more recent work suggests that word of potential accruals mispricing has spread. For instance, Beneish and Vargus (2002) find insiders profiting from the accruals information. Also, Collins, Gong, and Hribar (2003) document that stocks with high institutional ownership exhibit stock prices that reflect more accurately the persistence of accruals. Finally, using data from 1984 to 2003, Ali, Chen, Yao, and Yu (2008) provide evidence that some mutual funds have been successfully implementing the accruals strategy in the U.S. market.

If the anomaly is indeed exploited by investors, we can expect a significant decrease in its profitability over time. Figure 4.1 illustrates the strategy's performance for the U.S. As documented in prior research, the hedge strategy exhibits a relatively smooth path for the U.S., giving a cumulative wealth of 4.5 over the 13-year sample period. From the left panel in Figure 4.1, we conclude that most of the profits are made within the time period starting 1998 and ending 2003. The returns before 1998 were moderate and for the most recent time period the return path is starting to flatten out. To further examine the evolution of the U.S. accrual anomaly over time, we also compute the corresponding alpha via trailing Fama-French momentum regressions according to equation (2.3). We use a 36-months window and plot the resulting alpha in the right panel of Figure 4.1. The alpha for the U.S. strategy is slowly decreasing over time and is close to zero towards the end of our sample period, indicating a potential demise of the accrual anomaly for the U.S. market.

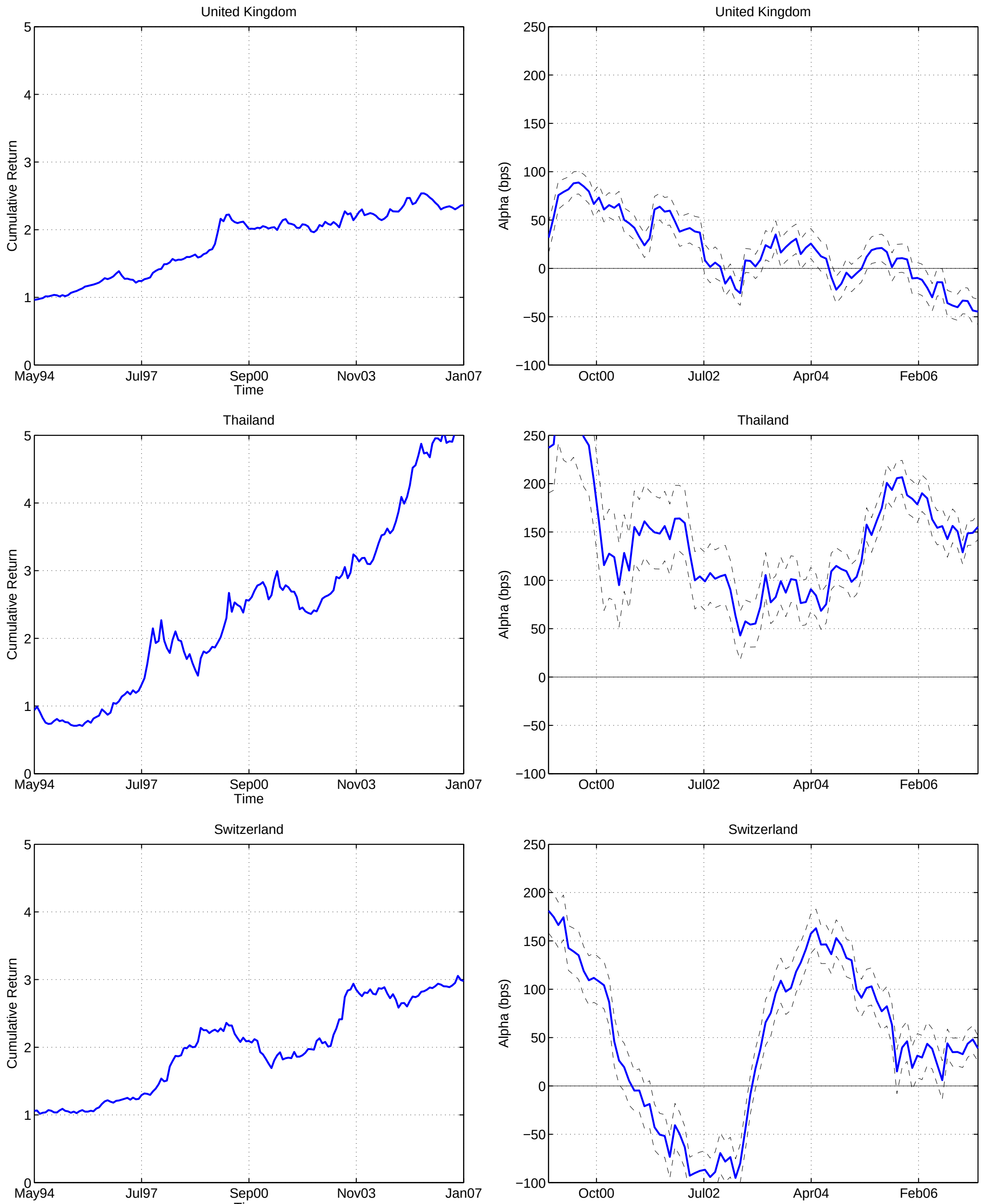
Figure 4.1: Cumulative Returns and Trailing Alphas for the U.S.
The left panel gives cumulative total return to the accruals hedge strategy for the U.S. covering the period from May 1994 to February 2007. In the right panel, we plot trailing Fama-French momentum alphas estimated from equation (2.3) using 36-months windows, giving us an effective time period starting May 1997 and ending February 2007. Dashed lines represent the 95%-confidence bands.



In the upper left panel of Figure 4.2, we observe a cumulative return pattern for the U.K. similar to the one in the U.S., but only until mid 2000. Our evidence for this subperiod seems to echo the findings of the robustness check in Chan, Chan, Jegadeesh, and Lakonishok (2006) using data from 1991 to 2000. They find that the U.K. sample supports their evidence of an accrual anomaly in the U.S. and conjecture that this result relates to the close resemblance of management compensation schemes and the behavior of research analysts and investors in these two countries. However, as we report in Table 3.2, the U.K. accrual anomaly can be subsumed by the Fama-French momentum factors. In any case, following 2000, the cumulative return of the hedge strategy for the U.K. is characterized by sideways moves. Inspecting the alphas of the Fama-French momentum regression in the lower right panel, we find that after July 2002 the U.K. alphas are practically zero and become even negative in the most recent time period.

Figure 4.2: Cumulative Returns and Trailing Alphas

The left panels give cumulative total return to the accruals hedge strategy for the U.K., Thailand, and Switzerland covering the period from May 1994 to February 2007. In the right panels, we plot trailing Fama-French momentum alphas estimated from equation (2.3) using 36-months windows, giving us an effective time period starting May 1997 and ending February 2007. Dashed lines represent the 95%-confidence bands.



On the other hand, the Thai strategy provides a total return that is comparable to the one of the U.S.. However, note that the strategy's volatility is higher and, more importantly, the anomaly does not appear to lose strength over time. While the U.S., the U.K., and Thailand operate under common law, it is surprising to also detect an accrual anomaly in Switzerland which is usually classified as being a code law country. However, this classification may be undue since Swiss companies are following different accounting practices, especially, following 2000. Hence, it seems questionable to compare companies on behalf of accrual levels arising from different accounting practices which may in turn explain the partially negative alpha of the Swiss accruals strategy.

Chapter 5

Price and Earnings Momentum

5.1 Review of Momentum Strategies

According to the Oxford Dictionary momentum is a force that is gained by movement. Price momentum entails the observation that past winning stocks continue to deliver superior returns in the short run while past losing stocks subsequently continue to disappoint. Likewise, earnings momentum refers to the observation of momentum in stock prices following the direction of analysts' earnings forecast revisions.

5.1.1 Price Momentum

Momentum in individual stock prices has first been documented by Jegadeesh and Titman (1993) and their approach to quantify price momentum has become the industry standard. They consider a portfolio that is long in the winner decile and short in the loser decile. These decile portfolios arise from several winner and loser portfolios based on overlapping time periods. The stocks are ranked monthly according to their performance over the last six months and assigned accordingly to the respective quintile portfolios. These are held for six months. Hence, the winner or loser decile of the associated price momentum strategy of a given month is made up of six portfolios. Jegadeesh and Titman (1993) find such a price momentum strategy to earn more than 1% above the risk-free rate per month. Even though the decile portfolios usually consist of smaller sized companies with high beta risk, the associated hedge strategy's return cannot be fully explained by significant size or market exposure. The fact that the momentum anomaly is not arbitraged away and still persists is even more intriguing, see Jegadeesh and Titman (2001).

In explaining the phenomenon of U.S. price momentum, Jegadeesh and Titman (2001) examine post-holding period return patterns of momentum portfolios. These patterns favor a behavioral explanation of momentum to be triggered from market participants' under- or overreaction to new information. Overreaction will drive stock prices to levels that are not fundamentally justified, giving rise to a subsequent reversion back to their initial level. On the other hand, given limited information processing capabilities, investors may underreact to news which may positively effect a company's fundamental value. Since overconfidence likely causes investors to cling to their original views, this fundamental news may only gradually transmit into the company's stock price. In this case, one obtains a flat post-holding period return to a momentum strategy.

Not only is the price momentum anomaly confined to the U.S., it has also been documented in several international studies, such as in Rouwenhorst (1998) for Europe and more recently in Griffin, Ji, and Martin (2003, 2005) for a large set of countries. While Rouwenhorst (1999) finds emerging markets to exhibit price momentum, Bekaert, Erb, Harvey, and Viskanta (1997) contend that momentum in these markets are less consistently profitable.

5.1.2 Earnings Momentum

Ball and Brown (1968) have first documented the phenomenon of post-earnings announcement drift which encompasses the tendency of stock prices to drift in the direction suggested by recent earnings surprises. This observation is most likely caused by irrational investors failing to fully appreciate the earnings information, which results in a delayed price response, see Bernard and Thomas (1989). While studies on the post-earnings announcement drift rely on some measure of realized earnings surprise, one may also resort to analysts' earnings forecasts as a more direct measure of earnings expectations. Doing so provides a more timely measure, given that non-U.S. companies usually report earnings on an annual basis as opposed to quarterly reporting. The investment strategy building on the above metric is typically referred to as earnings momentum.

The implementation of the earnings momentum strategy is similar to the one of price momentum. However, companies are not being ranked dependent on the level of prior returns but prior earnings revisions. As in Chan, Jegadeesh, and Lakonishok (1996), we build a moving average of cumulated revisions over the prior six months to capture the change in earnings expectations:

$$REV6_{it} = \sum_{j=0}^{6} \frac{f_{it-j} - f_{it-j-1}}{p_{it-j-1}} \tag{5.1}$$

where f_{it} is the consensus estimate in month t of the i-th company's earnings for the current fiscal year, as provided by the Institutional Brokers' Estimate System (I/B/E/S). The resulting difference, the monthly revision, is then scaled by the prior month's stock price. We go long in the highest earnings revisions quintile and short in the lowest quintile in any given month according to the value of $REV6_{it}$. Given a holding period of six months, the resulting hedge strategy's long leg consists of six overlapping portfolios, as does the short leg.

5.1.3 Linking Price and Earnings Momentum

It is straightforward to speculate as to whether price and earnings momentum may reflect the very same mispricing or behavioral bias. In fact, prior studies like Chan, Jegadeesh, and Lakonishok (1996) find that the U.S. momentum effect is concentrated around subsequent earnings announcements and show that price momentum may partially be explained by underreaction to earnings information. However, they contend that price momentum is not subsumed by earnings momentum since each ranking variable has some incremental predictive power for future returns. This view is shared by Griffin, Ji, and Martin (2005) who analyze both momentum strategies in an international context. Given that Hong and Swaminathan (2003) only detect price momentum in countries that also exhibit earnings momentum nevertheless makes the case for a closer relation of the two anomalies. Indeed, Chordia and Shivakumar (2006) show that U.S. price momentum appears to be a manifestation of earnings momentum.

5.2 Data

5.2.1 Sample Selection

We use a comprehensive sample of companies domiciled in 17 equity markets, 16 European markets and the U.S., covering the period from 1987 to 2007. All data has been gathered from Datastream including I/B/E/S earnings revisions data.

Table 5.1 contains information on the sample countries classified by region. We collect companies for each country by merging the live and dead research lists provided by Datastream on July 2nd, 2007 and thereby obtain a total number of 65,925 companies. To arrive at our final sample, we have pruned the initial country research lists as follows. First, we adjust each country list for secondary issues and cross-country listings to prevent double-counting. In particular, we extract 30,552 companies. Hence, only one half of the initial list does refer to major listings.

Table 5.1: Country Overview

The table contains descriptive information on the companies that have been domestically traded in the sample period (1987-2007). For further reference we may use abbreviated country codes (Abbr.). The screening of country lists depicts the evolution of the countries' samples. First, we give the *total* size of the country lists followed by the number of companies surviving the first screen for *Major* listings. The column headed *Region* contains the number of companies surviving the screen eliminating regional listings and the like. The *Final* screen excludes companies which exhibit free-floating market value below 10 million USD. We further describe this final sample giving the number of a country's dead companies (#Dead) and the number of companies with at least one I/B/E/S estimate in the sample period (#I/B/E/S), along with respective percentage values (%-Dead and %-I/B/E/S). The last column gives the earliest month with sufficient Fama-French data. The table provides information for the U.S. in Panel A, while Panel B covers European countries.

Country	Abbr.	Region	Screening of Country Lists				Sample: FMV> 10						Date
			Total	*Major*	*Region*	FMV> 10	#Dead	%Dead	#Return	%Return	#I/B/E/S	%I/B/E/S	FF
Panel A: USA													
USA	USA	America	36659	20030	7279	6272	2554	40.7%	6180	98.5%	4860	77.5%	Jul 92
Panel B: Europe													
Europe	EUR	Europe	29266	10522	9383	7019	1996	28.4%	6901	98.3%	5169	73.6%	
United Kingdom	UK	Europe	7677	3444	3232	2268	732	32.3%	2232	98.4%	1652	72.8%	Jul 87
Ireland	IRL	Europe	187	98	94	85	26	30.6%	83	97.6%	63	74.1%	Feb 91
Germany	GER	Europe	10740	1833	1525	1017	228	22.4%	991	97.4%	646	63.5%	Jan 88
Austria	A	Europe	360	177	161	119	31	26.1%	115	96.6%	80	67.2%	Jan 90
Switzerland	CH	Europe	1130	387	316	277	49	17.7%	274	98.9%	217	78.3%	Jan 90
France	FR	Europe	2643	1458	1368	945	258	27.3%	917	97.0%	631	66.8%	Jan 90
Italy	IL	Europe	794	390	365	345	95	27.5%	345	100 %	305	88.4%	Jan 90
Greece	GR	Europe	523	393	360	338	57	16.9%	338	100 %	234	69.2%	Jun 98
Spain	ES	Europe	311	204	180	170	51	30.0%	168	98.8%	160	94.1%	Feb 92
Portugal	POR	Europe	296	146	134	92	48	52.2%	91	98.9%	66	71.7%	Jun 97
Netherlands	NL	Europe	791	272	250	201	77	38.3%	199	99.0%	182	90.5%	Jan 90
Belgium	BEL	Europe	1000	288	263	206	40	19.4%	200	97.1%	129	62.6%	Jan 90
Sweden	SWE	Europe	1203	549	441	346	109	31.5%	344	99.4%	280	80.9%	Jan 90
Norway	NOR	Europe	585	328	284	254	98	38.6%	252	99.2%	219	86.2%	Jan 90
Denmark	DK	Europe	685	365	230	197	55	27.9%	197	100 %	167	84.8%	Jan 90
Finland	FN	Europe	341	190	180	159	42	26.4%	155	97.5%	138	86.8%	Mar 91
		All	65925	30552	16662	13291	4550	34.2%	13081	98.4%	10029	75.5%	
		Top 5	58922	27314	13845	10848	3881	35.8%	10664	98.3%	8094	74.6%	

Second, we screen for non-equity issues, i.e., we exclude investment trusts, ADRs, and the like. Third, we also exclude OTC stocks and stocks that are only listed on regional exchanges. Following these two screens 16,662 companies remain. We further exclude those having market capitalization below 10 million USD, which leaves us with a final sample of 13,291 companies. Almost one half are U.S. companies and the biggest five markets comprise some 80%. To avoid survivorship bias, the sample includes 4,550 “dead” companies, i.e., one third of the whole sample, ranging from 16.9% for Greece to 52.2% for Portugal. The label “dead” applies to companies in extreme distress and to those being merged, delisted, or converted.

Since we aim to investigate price and earnings momentum strategies, we additionally check the coverage of return and earnings revisions data. Unsurprisingly, the coverage for return data is close to 100% in each country, on average 98.4% of the companies do exhibit at least one return observation over the course of the sample period. As for the earnings estimates, these figures are more fragmentary. However, the average coverage still amounts to 75.5% spanning a range from 62.6% (Belgium) to 94.1% (Spain). Note that our sample contains a certain amount of penny stocks that will not be included in the momentum strategies. We do not discard them right away, since being a penny stock is not a static firm characteristic. In particular, we do not invest in companies with stock price below 5$ at the beginning of a given month. To give an idea of the investment universe's size over time, we provide the absolute number of companies to be considered for the momentum strategies across countries in Table 5.2. All in all, we have 59,394 firm-years for the momentum strategies of which one half is concentrated in the U.S. (32,905 firm-years), followed by France (4,255 firm-years) and the U.K. (4,188 firm-years). Note that the number of available companies increased over the years. However, the 1999 peak is followed by a slight setback.

5.2.2 Return Data

We consider monthly stock returns in local currency inclusive of dividends by employing total return figures. To represent the respective markets, we choose broad market indices as compiled by Datastream and 3-month-T-bills serve as a proxy for the risk-free rate. As we have already shown in Chapter 2 the price momentum effect cannot be detected when naïvely using raw Datastream data. Thus, we again follow Ince and Porter (2006) in adjusting the return data to allow for reasonable statistical and economic inferences.

Table 5.2: Country Universes by Year

The table gives the average number of companies which are considered for the momentum strategies. Panel A covers the U.S. and Panel B covers European countries.

Year	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	Σ #
Panel A: USA																					
USA	827	859	928	925	993	1104	1242	1366	1568	1804	2038	2172	2336	2260	2041	1827	2068	2117	2183	2247	32905
Panel B: European Countries																					
Europe	556	638	775	846	891	1038	1141	1204	1336	1521	1641	1761	1905	1845	1611	1358	1459	1570	1628	1885	26609
UK	144	128	110	118	129	141	169	167	197	234	264	256	300	268	207	171	227	282	310	366	4188
Ireland	3	5	4	2	3	2	3	5	10	13	16	16	15	15	12	13	16	17	17	20	207
Germany	93	92	105	110	120	188	242	224	213	230	252	264	257	262	237	175	185	202	206	250	3907
Austria	16	18	19	22	25	27	30	32	37	42	38	36	37	30	31	25	27	25	24	30	571
Switzerland	73	84	94	99	100	104	106	106	107	113	121	131	134	142	148	139	128	126	122	150	2327
France	62	82	116	131	133	156	154	165	191	220	256	277	310	327	298	264	261	265	276	311	4255
Italy	13	26	28	31	29	28	27	29	33	39	50	67	67	67	78	70	74	87	97	112	1052
Greece	0	0	0	0	0	0	15	59	79	75	70	82	109	61	50	38	48	43	45	56	830
Spain	13	23	54	69	68	64	62	67	68	69	74	90	90	91	86	79	82	83	81	83	1396
Portugal	0	0	0	0	8	24	26	28	31	36	37	40	42	29	15	10	7	10	12	18	373
Netherlands	54	79	86	91	91	93	95	98	103	110	113	120	132	127	106	86	92	91	88	91	1946
Belgium	30	29	29	31	34	38	39	41	44	45	51	63	66	73	76	64	65	74	68	74	1034
Sweden	19	16	29	31	33	34	48	58	73	101	108	125	131	127	90	71	85	89	92	106	1466
Norway	8	11	12	15	17	17	19	21	27	50	49	51	59	68	51	35	45	54	59	78	746
Denmark	23	37	70	72	77	96	75	67	74	89	89	82	86	88	66	57	54	61	70	68	1401
Finland	0	3	14	18	18	21	25	30	42	49	50	55	64	64	52	54	56	55	54	66	790
Σ	1378	1492	1698	1765	1878	2137	2377	2563	2897	3319	3676	3927	4235	4099	3644	3178	3520	3681	3804	4126	59394

Interestingly, we find our comprehensive sample to be hardly confounded by erroneous return data. For instance, the U.S. only requires to change 99 return observations which represents 0.01% of all observations. This fraction is even smaller for Europe for which we adjust 54 observations across all 16 countries. We assume that Datastream has significantly corrected the database in response to the objections of Ince and Porter (2006) in the meantime.[1] Still, the remaining issues might severely affect statistical inferences and weeding them out renders us even more comfortable with the quality of data.

5.3 Detecting Price and Earnings Momentum

5.3.1 Risk and Return

We next report descriptive statistics of momentum-based quintile portfolios by country. In computing momentum portfolio returns, we follow the standard approach of Jegadeesh and Titman (1993) that stipulates the use of overlapping portfolios as described in the previous section. Tables 5.3 and 5.4 give average monthly buy-and-hold return and volatility figures together with two risk proxies, size and beta.

First, we assess the profitability of the price momentum hedge strategy by considering the return differential along with its t-statistic. For the U.S., we obtain a monthly hedge return of 79 basis points at a monthly volatility of 4.4% giving rise to a t-statistic of 2.80. The latter is even higher for the European hedge strategy providing a return of 119 basis points per month but at a lower volatility. Further, using the t-statistic metric, we identify 12 European countries that have anomalous returns on a 5% level or better. If we relax the significance level to 10%, Norway appears to be anomalous as well, leaving Austria, Ireland, and Spain as the only countries for which price momentum is not significant, albeit positive. All in all, we recover prior evidence of pronounced international momentum effects as documented by Rouwenhorst (1998) and Griffin, Ji, and Martin (2003, 2005).

[1] In fact, according to an employee of Thomson Financial Services the return time series is constantly screened for possible glitches in the price, dividend, and adjustment factor history. In particular, the history of several U.S. OTC stocks has been fixed recently, which presumably accounted for a lot of issues detected by Ince and Porter (2006).

Table 5.3: Descriptive Statistics of Momentum Quintile Portfolios 1/2

The table gives average monthly buy-and-hold returns and volatility of quintile portfolios that are built monthly dependent on the price momentum ranking (left panel) or dependent on the earnings momentum ranking (right panel). All figures refer to the period from July 1987 to June 2007. We give the return differential of the respective hedge strategies along with the according t-statistic in parentheses. The table also gives the two risk proxies beta and size. Both are gathered using data of the whole period, in particular beta arises from a standard CAPM regression and size is measured as the average of log(marketvalue). Note that we do not compute the size proxy for the hedge strategies but give the t-statistic belonging to the return differential.

		Price Momentum Ranking					*Hedge Strategies*		*Earnings Momentum Ranking*						
Country		Lowest	2	3	4	Highest	Price	Earnings	Lowest	2	3	4	Highest		Country
USA	Return	0.93	1.15	1.21	1.27	1.72	0.79	0.58	1.27	1.16	1.10	1.43	1.85	Return	USA
	Volatility	6.48	4.41	3.98	4.17	5.98	4.40	2.17	5.50	4.40	3.82	4.21	4.91	Volatility	
	Beta	1.20	0.82	0.72	0.76	1.07	-0.14	-0.04	1.15	0.90	0.74	0.81	0.99	Beta	
	Size	19.77	20.29	20.46	20.49	20.21	(2.80)	(4.11)	19.47	20.17	20.61	20.60	20.04	Size	
Europe	Return	0.56	0.88	1.10	1.25	1.75	1.19	0.83	0.91	0.98	1.06	1.28	1.74	Return	Europe
	Volatility	5.76	4.24	3.93	4.02	4.77	3.69	1.71	4.82	4.28	3.82	3.74	3.99	Volatility	
	Beta	1.24	0.94	0.87	0.89	1.03	-0.21	-0.14	1.18	1.05	0.92	0.89	0.96	Beta	
	Size	20.32	20.92	21.16	21.29	21.15	(5.00)	(7.52)	19.96	21.02	21.43	21.43	20.63	Size	
UK	Return	0.54	0.96	1.09	1.19	1.42	0.88	0.78	0.89	0.88	1.22	1.27	1.67	Return	UK
	Volatility	5.28	4.32	4.18	4.30	4.92	3.70	2.10	4.42	4.14	3.99	3.88	4.01	Volatility	
	Beta	0.90	0.75	0.73	0.76	0.84	-0.06	-0.07	0.85	0.78	0.74	0.71	0.74	Beta	
	Size	24.75	24.94	24.95	24.84	24.57	(3.68)	(5.73)	24.54	24.91	25.11	24.89	24.46	Size	
Ireland	Return	1.73	1.43	1.78	0.98	1.84	0.39	1.23	1.12	1.73	1.49	1.71	2.49	Return	Ireland
	Volatility	6.91	5.72	5.62	6.20	6.23	5.74	5.67	6.59	4.99	4.97	5.38	5.60	Volatility	
	Beta	0.81	0.72	0.83	0.88	0.73	0.01	-0.15	0.87	0.67	0.68	0.81	0.74	Beta	
	Size	20.05	20.24	20.40	20.21	20.09	(1.04)	(3.36)	19.50	20.61	21.00	20.89	19.87	Size	
Germany	Return	0.22	0.66	0.80	0.99	1.25	1.03	0.76	0.49	0.62	0.73	0.84	1.24	Return	Germany
	Volatility	7.47	5.34	4.53	4.41	4.57	5.25	2.30	5.49	5.23	4.90	4.68	4.91	Volatility	
	Beta	1.51	1.11	0.92	0.88	0.90	-0.60	-0.02	1.20	1.15	1.06	1.02	1.08	Beta	
	Size	19.51	19.95	20.13	20.21	20.13	(3.04)	(5.10)	19.36	20.07	20.41	20.18	19.92	Size	
Austria	Return	1.17	1.21	1.24	1.46	1.50	0.33	0.58	1.17	1.33	1.06	1.11	1.76	Return	Austria
	Volatility	6.23	5.43	5.09	5.60	5.90	4.87	4.47	6.75	5.71	5.13	4.82	5.48	Volatility	
	Beta	1.15	1.12	1.07	1.11	1.18	0.03	-0.09	1.38	1.19	1.04	0.96	1.07	Beta	
	Size	19.00	19.39	19.60	19.70	19.65	(1.04)	(2.02)	19.06	19.45	19.64	19.61	19.59	Size	
Switzerland	Return	0.62	0.82	0.90	1.06	1.41	0.79	0.60	0.84	0.95	0.96	1.21	1.44	Return	Switzerland
	Volatility	6.35	4.99	4.60	4.81	5.40	4.16	3.02	5.83	4.87	4.26	4.37	4.69	Volatility	
	Beta	1.29	1.06	0.98	1.02	1.11	-0.18	-0.16	1.34	1.13	0.98	1.00	1.07	Beta	
	Size	19.90	20.24	20.36	20.49	20.39	(2.94)	(3.07)	19.67	20.36	20.55	20.50	20.20	Size	
France	Return	0.82	1.06	1.17	1.34	1.73	0.92	0.77	1.08	1.14	1.31	1.40	1.85	Return	France
	Volatility	7.37	5.61	5.04	5.16	5.74	4.66	2.81	6.38	5.64	5.16	5.00	5.21	Volatility	
	Beta	1.36	1.06	0.95	1.00	1.09	-0.27	-0.15	1.29	1.15	1.04	0.99	1.07	Beta	
	Size	19.52	20.14	20.31	20.31	20.13	(3.04)	(4.24)	19.21	20.07	20.33	20.35	19.90	Size	
Italy	Return	0.36	0.76	0.76	0.89	1.49	1.12	0.36	0.82	0.83	0.88	1.06	1.19	Return	Italy
	Volatility	7.71	6.53	6.18	5.73	6.41	5.16	3.22	6.61	6.54	6.62	6.13	5.93	Volatility	
	Beta	1.16	1.02	0.97	0.88	0.94	-0.22	-0.11	1.03	1.04	1.02	0.92	0.93	Beta	
	Size	20.28	20.56	20.66	20.61	20.45	(3.37)	(1.74)	19.87	20.69	20.78	20.69	20.19	Size	

Table 5.4: Descriptive Statistics of Momentum Quintile Portfolios 2/2

The table gives average monthly buy-and-hold returns and volatility of quintile portfolios that are built monthly dependent on the price momentum ranking (left panel) or dependent on the earnings momentum ranking (right panel). All figures refer to the period from July 1987 to June 2007. We give the return differential of the respective hedge strategies along with the according t-statistic in parentheses. The table also gives the two risk proxies beta and size. Both are gathered using data of the whole period, in particular beta arises from a standard CAPM regression and size is measured as the average of log(marketvalue). Note that we do not compute the size proxy for the hedge strategies but give the t-statistic belonging to the return differential.

		Price Momentum Ranking					*Hedge Strategies*		*Earnings Momentum Ranking*						
Country		Lowest	2	3	4	Highest	Price	Earnings	Lowest	2	3	4	Highest		Country
Greece	Return	0.75	1.40	1.53	2.21	2.91	2.16	0.33	1.69	1.23	1.99	1.57	1.93	Return	Greece
	Volatility	10.33	9.75	9.63	9.94	11.01	6.07	4.30	10.67	9.47	10.39	9.54	9.79	Volatility	
	Beta	0.81	0.78	0.78	0.77	0.83	0.02	0.01	0.84	0.75	0.82	0.76	0.77	Beta	
	Size	19.07	19.39	19.51	19.69	19.51	(5.53)	(1.17)	19.15	19.33	19.52	19.61	19.26	Size	
Spain	Return	1.08	1.15	1.32	1.43	1.54	0.46	0.85	0.88	0.84	1.21	1.35	1.84	Return	Spain
	Volatility	7.38	5.39	5.21	5.31	5.47	5.00	4.41	6.87	5.49	5.16	5.04	5.97	Volatility	
	Beta	1.14	0.90	0.86	0.85	0.86	-0.27	-0.16	1.13	0.92	0.85	0.83	0.91	Beta	
	Size	19.91	20.26	20.43	20.51	20.34	(1.42)	(2.98)	19.48	20.35	20.56	20.74	20.17	Size	
Portugal	Return	1.10	1.57	1.51	1.54	1.83	0.70	0.88	0.87	1.29	1.32	1.50	1.75	Return	Portugal
	Volatility	6.60	6.11	6.00	5.26	6.24	5.51	5.26	6.56	5.85	5.55	5.35	6.58	Volatility	
	Beta	0.91	0.84	0.81	0.71	0.77	-0.15	-0.06	0.93	0.79	0.77	0.71	0.81	Beta	
	Size	19.34	19.85	20.03	19.88	19.82	(1.97)	(2.59)	19.34	20.01	19.89	19.86	19.59	Size	
Netherlands	Return	0.84	1.18	1.31	1.35	1.72	0.87	0.85	1.11	1.16	1.20	1.58	1.96	Return	Netherlands
	Volatility	6.45	5.01	4.69	4.64	5.47	4.40	3.57	5.91	4.80	4.41	4.44	4.79	Volatility	
	Beta	1.22	0.98	0.91	0.89	1.00	-0.21	-0.17	1.19	0.97	0.90	0.87	0.95	Beta	
	Size	19.29	19.63	19.72	19.73	19.68	(3.08)	(3.69)	18.86	19.71	20.16	19.93	19.30	Size	
Belgium	Return	0.60	0.72	1.00	1.26	1.62	1.02	0.75	0.89	0.92	1.06	1.31	1.63	Return	Belgium
	Volatility	5.65	4.84	4.69	4.86	5.17	4.22	3.07	5.27	4.73	4.28	4.35	4.73	Volatility	
	Beta	1.28	1.15	1.14	1.17	1.17	-0.11	-0.02	1.30	1.21	1.10	1.09	1.20	Beta	
	Size	19.58	20.03	20.16	20.27	20.09	(3.73)	(3.77)	19.32	20.11	20.32	20.33	19.84	Size	
Sweden	Return	1.03	1.34	1.38	1.56	2.09	1.05	0.77	1.07	1.34	1.53	1.75	1.84	Return	Sweden
	Volatility	7.64	6.02	5.69	6.07	6.69	4.82	4.07	6.81	6.19	5.94	5.64	5.79	Volatility	
	Beta	0.91	0.72	0.67	0.71	0.76	-0.15	-0.13	0.82	0.75	0.71	0.65	0.67	Beta	
	Size	21.79	22.04	22.10	22.22	22.18	(3.38)	(2.95)	21.40	22.05	22.23	22.20	21.87	Size	
Norway	Return	1.25	1.40	1.42	1.18	1.81	0.75	0.43	1.46	1.22	1.02	1.55	1.85	Return	Norway
	Volatility	8.07	6.24	6.30	6.45	7.44	5.98	4.98	7.65	6.48	6.36	6.25	6.26	Volatility	
	Beta	1.05	0.81	0.81	0.83	0.94	-0.15	-0.15	1.01	0.87	0.83	0.79	0.79	Beta	
	Size	21.44	21.70	21.80	21.82	21.81	(1.94)	(1.35)	21.55	21.54	21.60	21.69	21.74	Size	
Denmark	Return	0.81	1.11	1.06	1.55	2.04	1.22	1.16	0.97	1.02	1.32	1.39	2.13	Return	Denmark
	Volatility	6.02	4.29	4.07	4.32	4.98	4.54	4.22	5.14	4.44	4.32	4.19	5.05	Volatility	
	Beta	1.35	1.08	1.05	1.05	1.15	-0.19	-0.03	1.29	1.13	1.07	1.03	1.16	Beta	
	Size	20.75	21.06	21.15	21.19	21.26	(4.18)	(4.27)	20.48	21.05	21.24	21.32	20.95	Size	
Finland	Return	0.92	1.33	1.85	1.54	1.93	1.01	1.18	1.01	1.08	1.21	1.44	2.19	Return	Finland
	Volatility	8.06	6.34	6.46	5.86	6.59	5.60	4.84	7.70	6.99	6.37	5.35	6.39	Volatility	
	Beta	1.08	0.86	0.89	0.80	0.85	-0.22	-0.11	1.05	0.99	0.88	0.75	0.83	Beta	
	Size	19.38	19.62	19.60	19.66	19.82	(2.79)	(3.78)	19.27	19.61	19.67	19.74	19.52	Size	

While the loser quintile is sometimes contributing to the return spread, we note that the lion's share is due to the winner quintile. This finding confirms prior evidence that a long-only investor may well benefit from an according momentum strategy. However, the extreme quintile portfolios are the riskiest across all countries, since the winner and loser portfolios prove to be more volatile than the portfolios with less extreme price momentum. To judge a systematic risk bias of these portfolios, we compute betas according to the classical regression

$$R_{it} - R_{Ft} = \alpha_i + \beta_i(R_{Mt} - R_{Ft}) + \varepsilon_{it}, \tag{5.2}$$

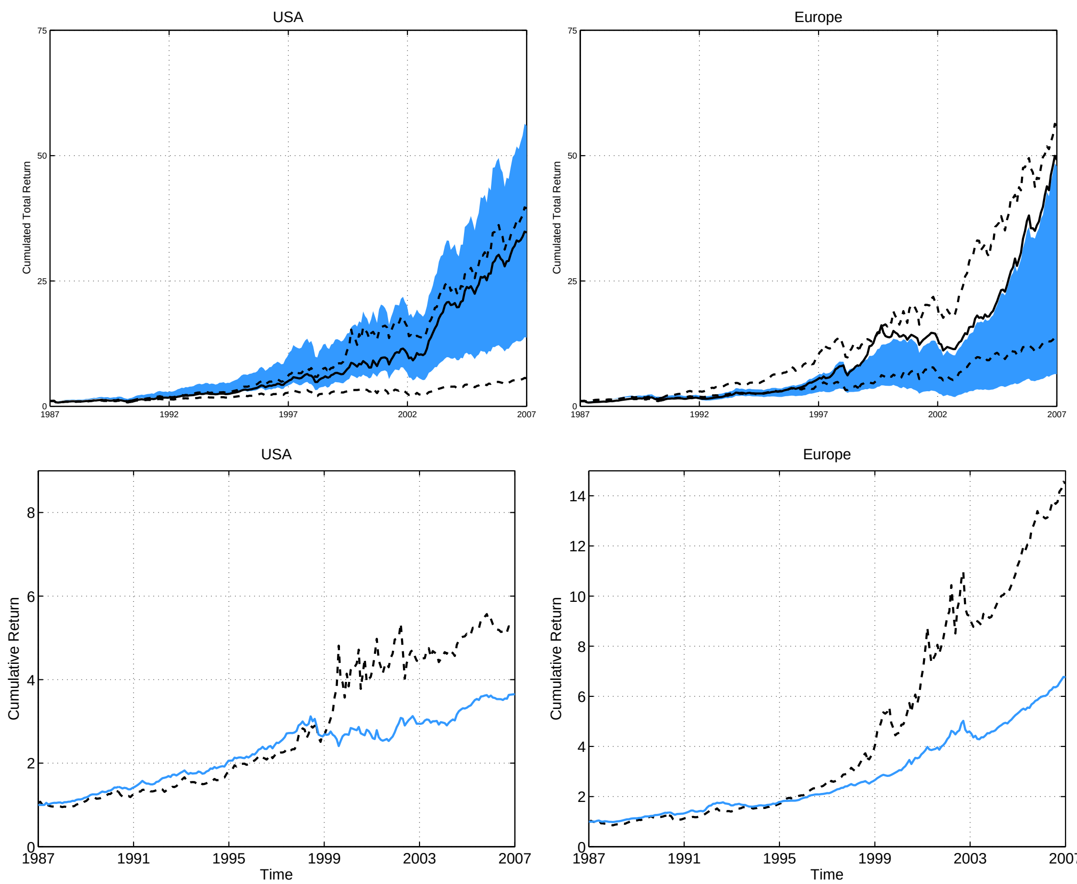
where R_{it} denotes the gross return of quintile i, R_{Ft} is the risk-free rate and R_{Mt} is the market return of the respective country. For more than half of the countries, the extreme quintile portfolios exhibit high betas, while the remaining portfolios appear to be homogeneous in terms of beta. Moreover, in 14 countries we obtain the highest betas for the loser quintile. Also, there is a size bias for the two extreme quintile portfolios. When we examine size, measured in terms of the logarithm of market value, we find that the two extreme portfolios are mostly populated by smaller companies. Again, the bias is more severe in the loser quintile, which may in turn explain its conspicuous market exposure. Concerning the price momentum strategy, we usually observe betas that are slightly negative suggesting that one may partially hedge against downside moves of the market.

Regarding earnings momentum, the U.S. strategy earns 58 basis points per month at a volatility that is only half the size of the price momentum volatility. Thus, the according t-statistic of 4.11 is more convincing. This observation of improved risk-adjusted performance also applies to the European earnings momentum strategy with a return of 83 basis points per month at 1.71% volatility, giving a t-statistic of 7.52. Across Europe, Tables 5.3 and 5.4 give rise to 13 significant return differentials while the remaining countries also show positive differentials. These usually reflect the general pattern of price momentum outperforming earnings momentum in terms of return at the cost of higher volatility. Even though earnings momentum exhibits less volatility, risk-mitigating effects with regard to market volatility do only occur in some countries. Compared to price momentum, these earnings momentum differentials seem to be driven less often by the short leg. Again, the extreme quintile portfolios are more risky than the middle portfolios. However, in contrast to price momentum the long leg has less beta exposure while the short leg of the earnings momentum strategy has a large exposure to this factor. Also, the earnings momentum strategy exhibits negative betas that are usually lower than those of the according price momentum strategy.

In the upper graphs of Figure 5.1, we plot the cumulative returns of the winner and loser quintiles of the earnings and price momentum strategies together with the evolution of an equally-weighted market portfolio. By inspecting the cumulative wealth of the extreme quintiles for the U.S., we find already strong support for the findings in Chordia and Shivakumar (2006), namely that price and earnings momentum are closely related. For both earnings and price momentum, the loser and the winner quintile portfolios move almost in sync. In addition, the loser portfolio stays well below the market portfolio and the winner portfolio stays well above it.

Figure 5.1: Cumulative Momentum Returns

The upper graphs give cumulative total returns to the winner and loser quintiles of the earnings momentum strategy in terms of a highlighted spread while the returns of the price momentum winners and losers are added as dashed lines. The performance of an equally-weighted market portfolio is given by the solid line. The lower graphs give cumulative total returns to the price momentum strategy (dashed line) and to the earnings momentum strategy (solid line). Results are for the period from July 1987 to June 2007.



We observe a similar behavior in Europe. However, both legs of the price momentum strategy are shifted upwards as compared to their earnings momentum counterparts. Also, inspecting the cumulative momentum returns for the U.S. and Europe over time in the lower graphs of Figure 5.1 confirms the above statements. Both, price and earnings momentum, seem to be closely tied. Over the nineties, the respective return paths nearly coincide. However, the earnings momentum strategy is smoother. While this observation has already been deduced from the descriptive statistics, we additionally learn that the higher volatility figures mainly arise over a short period following the burst of the technology bubble in 1999. Hence, though usually sailing in safe waters, a price momentum investor may experience very turbulent times with volatility well in excess of common market levels.

5.3.2 Time-Series Regressions

Since most of the hedge strategies are highly volatile, we wonder whether their high returns are solely compensating for risk. To further examine the performance of our strategies, we therefore check if the long-short portfolio returns can be attributed to common risk factors. We adopt the standard approach of Fama and French (1993) and estimate a regression model of the form

$$R_{Lt} - R_{St} = \alpha + \beta(R_{Mt} - R_{Ft}) + \gamma R_{SMBt} + \delta R_{HMLt} + \varepsilon_t, \tag{5.3}$$

where $R_{Lt} - R_{St}$ is the return difference of the respective hedge strategy, i.e., the long leg minus the short leg. Regarding the common risk factor portfolios we compute country-specific factors as follows: The market return R_{Mt} is represented by some broad market index, the size factor R_{SMBt} is mimicked by a small cap index minus the risk-free rate, $R_{SCt} - R_{Ft}$, and the value factor R_{HMLt} is the difference between a value index and the corresponding growth index, $R_{Vt} - R_{Gt}$. Given the factor structure in (5.3), we can identify the alpha generated by the hedge strategy net of common risk factors.

Table 5.5 displays the results of a Fama-French regression for price momentum according to equation (5.3) that uses 240 monthly returns spanning the period from July 1987 to June 2007. Across all countries, the risk factors explain most of the variation of the loser and winner quintiles' excess returns, thus confirming our descriptive analysis in the previous section. However, concerning the long-short strategies, we note that the model's explanatory power is generally low, confirming prior evidence as in Fama and French (1996).

Table 5.5: Time-Series-Regressions of Price Momentum Portfolios

The Table gives the results of a regression according to Equation (5.3) using 240 monthly returns ranging from July 1987 to June 2007 along with the according *t*-statistics. Portfolio 1 refers to the loser quintile, portfolio 5 refers to the winner quintile, and portfolio 5-1 is the long-short portfolio (winner-loser).

		Fama-French Model								
		α	β	γ	δ	$t(\alpha)$	$t(\beta)$	$t(\gamma)$	$t(\delta)$	Adj. R^2
USA	1	-0.90	1.00	0.34	0.08	-5.29	19.38	5.43	1.28	84.5
	5	0.11	0.82	0.34	-0.30	0.63	15.64	5.45	-5.06	81.0
	5-1	1.01	-0.18	0.01	-0.38	3.57	-2.07	0.08	-3.88	7.0
Europe	1	-0.41	0.76	0.41	0.21	-2.54	8.23	5.55	2.76	84.6
	5	1.05	0.52	0.45	-0.20	7.82	6.80	7.32	-3.19	84.7
	5-1	1.46	-0.24	0.04	-0.41	5.84	-1.68	0.33	-3.49	9.4
UK	1	-0.18	-0.33	1.19	0.04	-1.24	-3.05	11.77	0.64	82.0
	5	0.72	0.28	0.57	-0.29	4.67	2.41	5.28	-4.67	76.4
	5-1	0.90	0.60	-0.62	-0.32	4.02	3.65	-3.99	-3.64	12.0
Ireland	1	0.11	0.64	0.25	-0.02	0.29	6.81	2.53	-0.39	42.3
	5	0.35	0.65	0.17	-0.17	1.19	10.74	2.37	-3.58	54.6
	5-1	0.40	0.22	-0.27	-0.15	1.00	2.17	-2.51	-2.34	4.5
Germany	1	-0.95	1.37	0.15	-0.06	-3.83	14.55	1.67	-0.97	74.5
	5	0.33	0.52	0.47	0.03	2.40	9.80	9.66	0.77	78.8
	5-1	1.28	-0.85	0.33	0.09	4.36	-7.64	3.15	1.18	27.1
Austria	1	0.08	0.76	0.45	0.00	0.34	8.87	6.03	-0.04	65.0
	5	0.40	0.83	0.41	-0.06	2.03	12.12	6.75	-1.61	74.7
	5-1	0.32	0.08	-0.04	-0.06	0.98	0.69	-0.44	-0.95	-0.6
Switzerland	1	-0.55	1.11	0.15	0.15	-3.39	18.34	2.56	3.43	84.8
	5	0.38	1.05	0.11	-0.08	2.81	20.69	2.15	-2.26	85.4
	5-1	0.93	-0.06	-0.05	-0.24	3.56	-0.63	-0.48	-3.30	7.4
France	1	-0.85	1.03	0.41	0.19	-4.36	16.85	7.00	4.24	84.2
	5	0.31	0.95	0.18	-0.13	2.06	20.18	3.91	-3.73	84.6
	5-1	1.16	-0.08	-0.23	-0.33	4.19	-0.92	-2.81	-5.00	19.6
Italy	1	-0.65	1.27	-0.12	-0.05	-2.84	13.76	-1.25	-0.89	79.4
	5	0.54	0.75	0.22	-0.14	2.71	9.24	2.72	-3.13	77.0
	5-1	1.19	-0.52	0.34	-0.10	3.71	-3.97	2.59	-1.33	8.2
Greece	1	-1.19	0.52	0.40	-0.08	-4.04	10.64	7.22	-0.66	87.4
	5	0.97	0.55	0.43	-0.59	2.65	9.09	6.14	-4.01	82.9
	5-1	2.17	0.03	0.02	-0.51	4.49	0.40	0.25	-2.64	2.7
Spain	1	-0.45	0.85	0.34	-0.10	-1.91	9.77	3.59	-1.57	77.3
	5	0.20	0.73	0.16	-0.04	1.22	11.91	2.39	-0.99	79.6
	5-1	0.66	-0.12	-0.18	0.05	2.06	-1.01	-1.41	0.65	9.4
Portugal	1	-0.80	0.46	0.54	0.07	-2.40	5.59	8.75	0.82	61.1
	5	0.24	0.35	0.50	-0.18	0.70	4.06	7.84	-2.13	53.0
	5-1	1.02	-0.12	-0.04	-0.22	2.31	-1.05	-0.46	-1.98	2.2
Netherlands	1	-0.46	1.05	0.14	0.15	-2.73	17.15	2.24	3.85	84.0
	5	0.66	0.96	0.07	-0.06	3.93	15.70	1.15	-1.62	78.0
	5-1	1.13	-0.09	-0.07	-0.21	4.11	-0.91	-0.67	-3.37	9.3
Belgium	1	-0.66	1.10	0.19	0.04	-3.49	14.80	3.10	0.76	75.0
	5	0.52	0.92	0.27	-0.07	3.05	13.82	4.93	-1.55	76.2
	5-1	1.18	-0.18	0.08	-0.11	4.19	-1.60	0.89	-1.45	0.8
Sweden	1	-0.52	0.74	0.29	0.07	-2.10	13.51	4.22	1.81	75.5
	5	0.70	0.61	0.25	0.04	2.83	11.32	3.66	1.20	68.7
	5-1	1.22	-0.13	-0.04	-0.02	3.95	-1.86	-0.48	-0.50	4.0
Norway	1	-0.51	0.73	0.32	0.19	-1.69	8.55	4.03	3.18	69.9
	5	0.27	0.73	0.25	-0.02	0.95	9.94	3.51	-0.32	67.3
	5-1	1.06	-0.19	0.07	-0.20	2.67	-1.65	0.67	-2.48	3.9
Denmark	1	-0.70	0.84	0.49	-0.09	-2.99	8.16	6.19	-1.78	66.1
	5	0.65	0.89	0.25	-0.11	3.40	10.57	3.85	-2.84	67.2
	5-1	1.34	0.05	-0.24	-0.03	4.54	0.37	-2.40	-0.42	3.3
Finland	1	-0.71	0.85	0.25	-0.05	-2.56	8.90	2.68	-1.53	75.9
	5	0.54	0.32	0.57	-0.09	2.46	4.31	7.85	-3.94	77.6
	5-1	1.24	-0.52	0.32	-0.05	3.34	-4.07	2.60	-1.17	8.6

Table 5.6: Time-Series-Regressions of Earnings Momentum Portfolios

The Table gives the results of a regression according to Equation (5.3) using 240 monthly returns ranging from July 1987 to June 2007 along with the according t-statistics. Portfolio 1 refers to the negative earnings revisions quintile, portfolio 5 refers to the positive earnings revision quintile, and portfolio 5-1 is the long-short portfolio (positive-negative).

		Fama-French Model								
		α	β	γ	δ	$t(\alpha)$	$t(\beta)$	$t(\gamma)$	$t(\delta)$	Adj. R^2
	1	-0.63	1.00	0.22	0.12	-6.10	27.17	5.30	3.38	92.5
USA	5	0.22	0.75	0.33	-0.01	1.80	17.50	6.85	-0.16	87.3
	5-1	0.85	-0.25	0.11	-0.12	6.15	-5.12	2.01	-2.67	14.5
	1	-0.15	0.72	0.38	0.14	-1.59	12.73	8.56	3.06	92.5
Europe	5	0.89	0.47	0.42	0.03	10.14	9.13	10.25	0.82	90.9
	5-1	1.05	-0.25	0.04	-0.10	9.68	-3.94	0.70	-2.07	24.3
	1	0.04	0.11	0.72	-0.08	0.36	1.27	8.60	-1.70	83.5
UK	5	0.85	-0.06	0.77	0.00	7.33	-0.65	9.46	0.07	80.8
	5-1	0.80	-0.17	0.06	0.08	6.00	-1.67	0.60	1.56	5.4
	1	-0.53	0.59	0.33	-0.11	-1.33	4.45	2.75	-1.98	45.7
Ireland	5	1.05	0.50	0.32	-0.05	3.75	5.93	3.92	-1.08	47.7
	5-1	1.45	-0.19	0.03	0.02	3.14	-1.24	0.24	0.34	0.2
	1	-0.66	0.84	0.40	0.08	-4.25	12.12	6.54	1.87	81.8
Germany	5	0.20	0.64	0.47	0.01	1.57	11.35	9.44	0.29	84.9
	5-1	0.87	-0.20	0.07	-0.07	5.80	-3.00	1.22	-1.71	4.8
	1	-0.17	1.02	0.37	0.08	-0.75	11.78	5.02	1.95	73.9
Austria	5	0.71	0.67	0.43	0.01	3.49	8.77	6.75	0.13	69.6
	5-1	0.89	-0.35	0.07	-0.08	3.07	-3.28	0.73	-1.48	7.9
	1	-0.50	1.33	0.00	0.01	-3.87	19.74	-0.01	0.33	89.2
Switzerland	5	0.31	0.85	0.22	0.00	2.99	15.62	4.52	-0.08	89.0
	5-1	0.81	-0.48	0.22	-0.01	4.37	-4.92	2.55	-0.27	14.8
	1	-0.68	1.05	0.25	0.16	-4.65	19.97	5.41	4.93	89.1
France	5	0.28	0.94	0.14	-0.01	2.25	20.61	3.39	-0.51	87.8
	5-1	1.00	-0.13	-0.10	-0.18	5.86	-2.18	-1.85	-4.51	21.7
	1	-0.32	0.88	0.15	0.08	-1.85	11.64	1.97	2.03	84.0
Italy	5	0.10	0.99	-0.07	0.07	0.65	14.78	-1.00	1.99	84.7
	5-1	0.42	0.10	-0.22	-0.01	2.03	1.14	-2.40	-0.24	4.4
	1	-0.38	0.52	0.45	-0.20	-1.24	10.21	7.63	-1.55	86.7
Greece	5	0.11	0.45	0.45	-0.33	0.37	9.45	8.25	-2.84	86.7
	5-1	0.45	-0.06	-0.01	-0.13	1.34	-1.10	-0.17	-0.95	3.0
	1	-0.66	0.78	0.41	-0.06	-3.87	11.84	5.83	-1.28	86.7
Spain	5	0.40	0.82	0.10	-0.05	1.95	10.80	1.23	-0.86	73.7
	5-1	1.03	-0.02	-0.25	0.01	3.65	-0.22	-2.11	0.15	9.5
	1	-1.02	0.43	0.60	0.01	-3.46	5.90	11.03	0.07	67.2
Portugal	5	0.04	0.45	0.44	-0.08	0.10	4.70	6.27	-0.81	45.9
	5-1	1.06	0.01	-0.16	-0.08	2.58	0.13	-2.09	-0.80	2.0
	1	-0.29	0.87	0.29	0.10	-1.92	12.78	4.66	2.86	85.6
Netherlands	5	0.79	0.90	0.06	-0.04	5.58	13.98	1.08	-1.34	80.5
	5-1	1.08	0.03	-0.23	-0.14	4.89	0.31	-2.47	-2.80	13.9
	1	-0.42	1.04	0.24	0.01	-2.42	11.91	3.68	0.25	76.6
Belgium	5	0.46	0.86	0.30	-0.03	3.21	12.23	5.72	-0.70	81.0
	5-1	0.88	-0.17	0.06	-0.04	4.19	-1.67	0.80	-0.68	0.7
	1	-0.50	0.62	0.32	0.11	-2.25	11.61	5.00	3.36	75.8
Sweden	5	0.43	0.41	0.40	0.10	2.09	8.34	6.71	3.30	71.7
	5-1	0.93	-0.21	0.08	-0.01	3.55	-3.32	1.02	-0.26	6.5
	1	-0.23	0.70	0.31	0.12	-0.82	8.72	4.22	2.17	71.2
Norway	5	0.44	0.51	0.30	0.04	1.75	7.09	4.42	0.74	64.8
	5-1	0.71	-0.18	-0.03	-0.07	2.16	-1.88	-0.35	-1.01	6.6
	1	-0.58	0.92	0.34	0.00	-3.26	10.77	5.34	0.00	73.8
Denmark	5	0.64	0.97	0.17	-0.05	3.00	9.47	2.20	-1.15	60.6
	5-1	1.23	0.05	-0.17	-0.05	4.32	0.37	-1.70	-0.87	1.3
	1	-0.52	0.80	0.26	0.03	-2.06	9.25	3.16	0.96	77.5
Finland	5	0.88	0.32	0.55	-0.02	4.15	4.40	7.73	-0.79	76.5
	5-1	1.40	-0.48	0.28	-0.05	4.44	-4.39	2.71	-1.30	10.1

The resulting alphas are positive and significant at the 5%-level for 15 out of 17 countries, whereas Ireland and Austria are the exception to the rule. Note that the hedge strategies are also promising in terms of economical significance. Except for Austria, Ireland, and Spain, 14 countries generate monthly alphas in excess of 90 basis points, the Greek alpha even amounts to 217 basis points, followed by 134 basis points for Denmark and 128 basis points for Germany. Across countries, we note that the alphas are mostly driven equally by the long and the short leg, with a slight tendency towards the long leg. However, the U.S. alpha of 101 basis points is almost entirely due to the short leg.

Table 5.6 gives the analogous results of the Fama-French regression for earnings momentum which is not captured by common risk factors as well. All countries exhibit positive alphas that are significant on a 5%-level in 16 cases—the odd one out is Greece. Hence, this analysis significantly hardens our pure return diagnostics. As for the sources to the earnings momentum alphas, we note that long and short legs contribute in equal shares.

To further examine the evolution of both hedge strategies over time, we compute the related alphas for the U.S. and Europe via trailing Fama-French regressions according to equation (5.3). We use a 36-month window and plot the resulting alphas in the upper graphs of Figure 5.2 for price momentum and in the lower graphs of Figure 5.2 for earnings momentum. To address statistical significance, we additionally provide 95% confidence bands. Regarding price momentum, the hedge strategies' alphas prove to be consistently positive throughout the sample period. While the evolution of price momentum alphas is rather volatile, earnings momentum alphas behave more steadily. Interestingly, the U.S. momentum strategies have experienced severe drawdowns at the end of the nineties while European momentum strategies have not faltered.

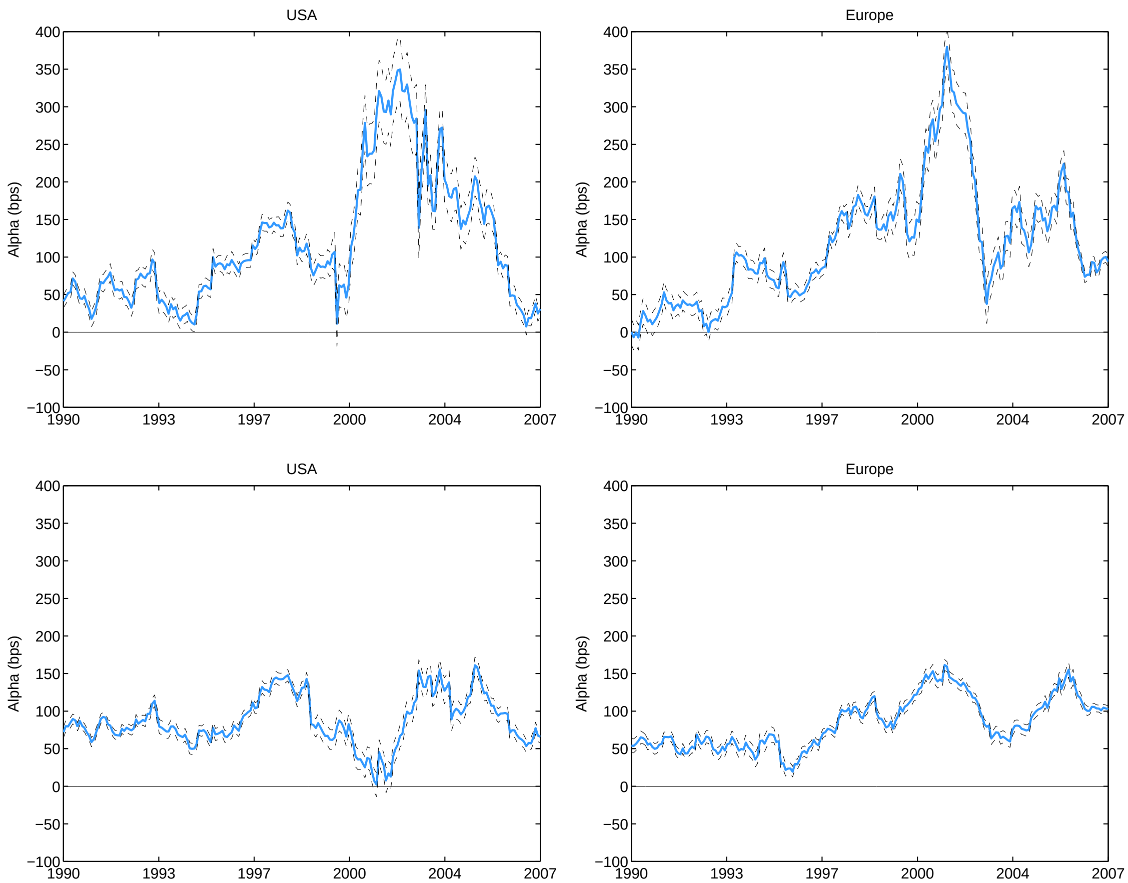
5.4 Momentum Strategies and Data Snooping

From the previous section we learn that 15 out of 17 countries exhibit positive and significant price momentum alphas and 16 exhibit positive and significant earnings momentum alphas. However, these alphas may be spurious since they arise from single hypothesis tests performed for each country. Therefore, we will subject both momentum strategies to the methods of Chapter 3 that additionally account for multiple testing.

To control the FWE, we consider the k-StepM method for $k = 1$ which is the appropriate choice given the number of strategies under study. To control the FDP,

Figure 5.2: Trailing Alphas of Momentum Hedge Portfolios

We plot trailing Fama-French momentum alphas estimated from equation (5.3) using 36-months windows, thus results cover July 1990 to June 2007. Also, we give 95%-confidence bands (dashed lines). The upper graphs refer to the price momentum strategy, the lower graphs refer to the earnings momentum strategy, respectively.



we pursue the FDP-StepM$_\gamma$ using $\gamma = 0.1$. We keep the significance level constant at 5% across all multiple testing procedures and we present results for the return of the hedge strategies as well as their alphas arising from the Fama-French time series regressions. To account for potential serial correlation in the return series, we use a kernel variance estimator based on the Parzen kernel to studentize the test statistics, see Andrews (1991). The bootstrap method is the stationary bootstrap with an average block size of 12 months.[2]

Panel A of Table 5.7 reports the countries' return statistics for price momentum. We provide the lower confidence band c_l for the returns using studentized test statistics according to the StepM and FDP-StepM$_\gamma$ method, respectively. Since we are in a

[2]Using the stationary bootstrap with an average block size of 6 months leaves results virtually unchanged.

one-sided test setting, we give the lower limits of the confidence interval as computed in the last step of the respective method. The value in the column labeled rej equals 1 if $0 \notin [c_l, \infty)$, which indicates the rejection of capital market efficiency and suggests the presence of an anomaly in the respective country.

Concerning the results for the price momentum returns, we observe 13 rejections by the StepM method. Thus, the FDP-StepM$_\gamma$ is not equivalent to the StepM, since the number of rejections exceeds nine. Moreover, the FDP-StepM$_\gamma$ rejects market efficiency for 15 countries. Panel B of Table 5.7 displays the multiple testing results using the Fama-French price momentum alphas as test statistics. With this metric, price momentum is found to be overwhelmingly robust to data snooping. Already the StepM method yields 16 rejections of capital market efficiency. Hence, the results mirror those of the naïve screen that are also obtained using the FDP-StepM$_\gamma$.

As for the earnings momentum strategies, Table 5.7 reveals results that are qualitatively similar to the ones obtained for price momentum. However, considering returns as test statistic, the StepM gives only nine rejections of capital market efficiency, while the FDP-StepM$_\gamma$ method rejects 16 countries. Considering alphas as test statistic, the StepM method detects 15 and the FDP-StepM$_\gamma$ method 16 significant alphas.

To conclude, the detected price and earnings momentum anomalies are confirmed by our battery of tests that account for multiple testing issues. By and large, both phenomena prove to be quite persistent and raise the need of sound economic inference.

Table 5.7: Multiple Testing in International Momentum Strategies

The table gives the lower confidence band c_l for the returns as obtained by the StepM method and the FDP-StepM$_{0.1}$using studentized test statistics as illustrated in Section 3.1. The rej-columns contain the resulting decision where 1 indicates rejection of $\theta_s = 0$ (capital market efficiency). Panel A provides results for returns as test statistics and Panel B provides results for Fama-French alphas as test statistics.

	Price Momentum					Earnings Momentum				
Country	θ_s	*StepM*		*FDP-StepM*$_{0.1}$		θ_s	*StepM*		*FDP-StepM*$_{0.1}$	
		c_l	rej	c_l	rej		c_l	rej	c_l	rej
Panel A: Return										
USA	0.0079	0.0027	1	0.0048	1	0.0058	0.0018	1	0.0037	1
Europe	0.0119	0.0059	1	0.0082	1	0.0083	0.0046	1	0.0064	1
UK	0.0088	0.0024	1	0.0049	1	0.0078	0.0040	1	0.0058	1
Ireland	0.0039	-0.0040	0	-0.0010	0	0.0123	-0.0015	0	0.0051	1
Germany	0.0103	0.0033	1	0.0060	1	0.0076	0.0030	1	0.0052	1
Austria	0.0033	-0.0043	0	-0.0014	0	0.0058	-0.0028	0	0.0013	1
Switzerland	0.0079	0.0007	1	0.0035	1	0.0060	-0.0006	0	0.0025	1
France	0.0092	0.0027	1	0.0052	1	0.0077	0.0031	1	0.0053	1
Italy	0.0112	0.0043	1	0.0070	1	0.0036	-0.0021	0	0.0006	1
Greece	0.0216	0.0110	1	0.0151	1	0.0033	-0.0065	0	-0.0019	0
Spain	0.0046	-0.0029	0	0.0000	0	0.0085	0.0000	0	0.0040	1
Portugal	0.0070	-0.0017	0	0.0017	1	0.0088	-0.0008	0	0.0038	1
Netherlands	0.0087	0.0019	1	0.0046	1	0.0085	0.0006	1	0.0044	1
Belgium	0.0102	0.0034	1	0.0060	1	0.0075	0.0022	1	0.0047	1
Sweden	0.0105	0.0036	1	0.0063	1	0.0077	-0.0003	0	0.0035	1
Norway	0.0075	-0.0011	0	0.0022	1	0.0043	-0.0050	0	-0.0005	0
Denmark	0.0122	0.0059	1	0.0084	1	0.0116	0.0032	1	0.0072	1
Finland	0.0101	0.0017	1	0.0050	1	0.0118	0.0032	1	0.0073	1
Panel B: Fama-French Alpha										
USA	0.0101	0.0046	1	0.0067	1	0.0085	0.0054	1	0.0067	1
Europe	0.0146	0.0082	1	0.0106	1	0.0105	0.0079	1	0.0090	1
UK	0.0090	0.0037	1	0.0057	1	0.0080	0.0052	1	0.0063	1
Ireland	0.0040	-0.0041	0	-0.0011	0	0.0145	0.0030	1	0.0076	1
Germany	0.0128	0.0060	1	0.0086	1	0.0087	0.0049	1	0.0064	1
Austria	0.0032	-0.0036	0	-0.0010	0	0.0089	0.0030	1	0.0054	1
Switzerland	0.0093	0.0025	1	0.0051	1	0.0081	0.0035	1	0.0054	1
France	0.0116	0.0063	1	0.0083	1	0.0100	0.0063	1	0.0078	1
Italy	0.0119	0.0056	1	0.0080	1	0.0042	-0.0003	0	0.0015	1
Greece	0.0217	0.0120	1	0.0156	1	0.0045	-0.0031	0	0.0000	0
Spain	0.0066	0.0008	1	0.0030	1	0.0103	0.0042	1	0.0067	1
Portugal	0.0102	0.0006	1	0.0042	1	0.0106	0.0031	1	0.0061	1
Netherlands	0.0113	0.0057	1	0.0078	1	0.0108	0.0052	1	0.0074	1
Belgium	0.0118	0.0052	1	0.0077	1	0.0088	0.0045	1	0.0062	1
Sweden	0.0122	0.0055	1	0.0080	1	0.0093	0.0035	1	0.0058	1
Norway	0.0106	0.0025	1	0.0056	1	0.0071	0.0003	1	0.0030	1
Denmark	0.0134	0.0077	1	0.0099	1	0.0123	0.0055	1	0.0082	1
Finland	0.0124	0.0047	1	0.0076	1	0.0140	0.0077	1	0.0103	1
Σ		*Return*	13		15			9		16
		Alpha	16		16			16		17

5.5 Linking Price and Earnings Momentum

Having ruled out data snooping biases as possible explanations to the momentum effects, we will further delve into the economic nature of these phenomena. In fact, one may wonder whether both price and earnings momentum may be traced back to similar sources, be it a behavioral bias or a compensation for risk.

5.5.1 Correlation of Price and Earnings Momentum

When inspecting the cumulative returns in Figure 5.1, we have already noted that price and earnings momentum do follow very similar return paths. To quantify this similarity, we simply compute the correlation of selected price and earnings momentum portfolios in Table 5.8. In particular, we compare portfolios with identical price and earnings momentum ranking. For instance, in the U.S. we observe a correlation of 0.933 between the loser portfolio and the portfolio with the lowest earnings revisions. The winner portfolio is also highly correlated with the highest earnings revision portfolio, exhibiting a correlation of 0.902. Unsurprisingly, these figures are significantly different from zero. Moreover, this relation also holds in the remaining countries with the same order of magnitude. Most of the correlations range between 0.8 and 0.95. However, among the different countries' quintile portfolios, the winner quintiles usually have the smallest correlation.

Given these results, we suspect the price and earnings momentum hedge strategies to be positively correlated as well. Indeed, while Greece unsurprisingly exhibits rather zero correlation, all of the remaining time series of returns exhibit significantly positive correlation with correlation coefficients between 0.161 and 0.670. Among the 17 countries we find ten (seven) with correlation in excess of 0.3 (0.4). We also compute the correlation of price and earnings momentum alphas using the respective time-series arising from the trailing Fama-French regressions of Section 5.3. While the resulting correlation figures often exceed those of the return time series, Spain has a negative correlation and for two countries, the alphas' correlation is not distinguishable from zero. These countries are Greece and the U.S.. Especially for the U.S., this observation is unanticipated given a return time series correlation of 0.319. Nevertheless, the general pattern of alpha correlations is consistent with the return correlations, giving 15 significant figures ranging from 0.224 (Switzerland) to 0.630 (France).

Table 5.8: Correlation of Price and Earnings Momentum Returns

The table gives correlation figures of quintile portfolio returns built monthly dependent on the price and earnings momentum ranking. We compare momentum portfolios that belong to the same quintile ranking. The p-Value arises from a test of zero correlation in the return of the respective portfolios. The two rightmost columns give the correlation coefficients for the return and the Fama-French alpha of both strategies.

		Price-Earnings Momentum Ranking					*Hedge Strategies*	
Country		Lowest	2	3	4	Highest	Return	Alpha
USA	Correlation	0.933	0.967	0.971	0.948	0.902	0.319	0.099
	p-Value	0	0	0	0	0	0	0.157
Europe	Correlation	0.952	0.978	0.970	0.976	0.932	0.651	0.825
	p-Value	0	0	0	0	0	0	0
UK	Correlation	0.898	0.952	0.959	0.956	0.869	0.161	0.521
	p-Value	0	0	0	0	0	0.013	0
Ireland	Correlation	0.749	0.772	0.830	0.754	0.804	0.348	0.624
	p-Value	0	0	0	0	0	0	0
Germany	Correlation	0.928	0.958	0.919	0.893	0.917	0.508	0.538
	p-Value	0	0	0	0	0	0	0
Austria	Correlation	0.813	0.848	0.881	0.867	0.864	0.262	0.573
	p-Value	0	0	0	0	0	0	0
Switzerland	Correlation	0.948	0.946	0.951	0.954	0.907	0.567	0.224
	p-Value	0	0	0	0	0	0	0.001
France	Correlation	0.952	0.969	0.966	0.962	0.935	0.670	0.630
	p-Value	0	0	0	0	0	0	0
Italy	Correlation	0.904	0.942	0.924	0.932	0.858	0.253	0.328
	p-Value	0	0	0	0	0	0	0
Greece	Correlation	0.924	0.968	0.964	0.960	0.932	0.076	0.095
	p-Value	0	0	0	0	0	0.344	0.273
Spain	Correlation	0.885	0.950	0.955	0.956	0.861	0.177	-0.439
	p-Value	0	0	0	0	0	0.007	0
Portugal	Correlation	0.866	0.830	0.867	0.873	0.783	0.280	0.573
	p-Value	0	0	0	0	0	0	0
Netherlands	Correlation	0.947	0.954	0.934	0.943	0.913	0.663	0.616
	p-Value	0	0	0	0	0	0	0
Belgium	Correlation	0.908	0.916	0.936	0.915	0.865	0.471	0.551
	p-Value	0	0	0	0	0	0	0
Sweden	Correlation	0.878	0.913	0.915	0.937	0.881	0.318	0.486
	p-Value	0	0	0	0	0	0	0
Norway	Correlation	0.847	0.891	0.834	0.854	0.852	0.240	0.617
	p-Value	0	0	0	0	0	0	0
Denmark	Correlation	0.861	0.888	0.869	0.813	0.839	0.454	0.313
	p-Value	0	0	0	0	0	0	0
Finland	Correlation	0.895	0.907	0.902	0.876	0.899	0.541	0.528
	p-Value	0	0	0	0	0	0	0

5.5.2 Does Earnings Momentum Subsume Price Momentum?

So far we have compiled considerable evidence that price and earnings momentum are closely connected in the U.S. and several European markets. In fact, Chordia and Shivakumar (2006) show that the U.S. price momentum alpha vanishes when additionally controlling for earnings momentum, while the U.S. earnings momentum alpha is robust when vice versa controlling for price momentum. Chordia and Shivakumar (2006) thus reason that price momentum is just a noisy proxy for earnings momentum. While this reasoning is quite persuasive, we wonder whether this observation carries over to other markets. Therefore, when testing for price momentum, we extend the Fama-French setting of Equation (5.3) to a four-factor model by adding an earnings momentum factor:

$$R_{Lt} - R_{St} = \alpha + \beta(R_{Mt} - R_{Ft}) + \gamma R_{SMBt} + \delta R_{HMLt} + \zeta R_{PMNt} + \varepsilon_t, \qquad (5.4)$$

where R_{PMNt} refers to the returns to the earnings momentum strategy (positive minus negative earnings revisions). Accordingly, Table 5.9 contrasts the Fama-French results to those of the above four-factor model for all countries' respective hedge strategies. For the U.S. and the aggregate European strategy we additionally give the results for the quintile portfolios. While the returns of the quintile portfolios are usually reasonably captured by the Fama-French factors, the returns of the price momentum strategies are not. Even though these strategies sometimes load to one common factor or another, the adjusted R^2s are typically quite low. Only for the U.K., France, and Germany do we observe two-digit adjusted R^2s.

Considering the alphas of quintile portfolios, we note a monotonic increase from loser to winner portfolios. For instance, the monthly U.S. price momentum alpha of 101 basis points results from -90 basis points for the loser quintile and from 11 basis points from the winner quintile. However, this huge spread is fairly persistent when controlling for the earnings momentum factor. The loser quintile's alpha is -80 basis points and the winner quintile's alpha reduces to 1 basis point. As a consequence, the U.S. price momentum is still significant under the four-factor model, contrasting with the results of Chordia and Shivakumar (2006).

The general pattern in Europe is different. For instance, for the European strategy we observe the following. While the Fama-French model attains an adjusted R^2 of 9.4%, the four-factor model explains 42.9% of the variation in European price momentum returns, cutting down the Fama-French alpha of 146 basis points to insignificant 16 basis points. Across all countries, the addition of the earnings momentum strategy in (5.4) seems reasonable, since many portfolios exhibit significant loadings to this factor. In particular, the adjusted R^2 of the hedge strategies usually increases by a considerable amount. In this sense, all countries' price momentum alphas are clearly reduced in the four-factor model and so are the corresponding t-statistics. The latter reductions imply statistical insignificance in seven out of 16 European countries: The price momentum alphas of Germany, Switzerland, France, Spain, Portugal, the Netherlands, and Finland are subsumed by the respective earnings momentum factor.

Table 5.9: Time-Series-Regressions of Price Momentum Portfolios

The table's left panel gives the results of a regression according to Equation (5.3) using 240 monthly returns ranging from July 1987 to June 2007 followed by the according t-statistics. The right panel gives the results of a regression according to Equation (5.4). We use the country abbreviations introduced in Table 5.1. We give the quintile portfolios 1 (loser) to 5 (winner) together with the long-short portfolio (winner-loser).

		Fama-French Model									*4-Factor Model*										
		α	β	γ	δ	$t(\alpha)$	$t(\beta)$	$t(\gamma)$	$t(\delta)$	Adj. R^2	α	β	γ	δ	ζ	$t(\alpha)$	$t(\beta)$	$t(\gamma)$	$t(\delta)$	$t(\zeta)$	Adj. R^2
USA	1	-0.90	1.00	0.34	0.08	-5.29	19.38	5.43	1.28	84.5	-0.80	0.99	0.32	0.06	-0.17	-4.20	15.09	4.58	0.94	-2.02	83.7
	2	-0.24	0.75	0.14	0.21	-2.10	21.70	3.30	5.33	84.8	-0.30	0.72	0.18	0.23	0.16	-2.38	16.68	4.03	6.01	2.83	83.7
	3	-0.07	0.69	0.07	0.19	-0.63	19.44	1.63	4.75	80.3	-0.17	0.63	0.15	0.23	0.27	-1.43	15.39	3.54	6.22	5.10	80.5
	4	-0.04	0.70	0.12	0.07	-0.34	18.99	2.64	1.57	81.0	-0.15	0.62	0.22	0.11	0.32	-1.33	15.50	5.31	3.07	6.38	83.0
	5	0.11	0.82	0.34	-0.30	0.63	15.64	5.45	-5.06	81.0	0.01	0.74	0.45	-0.26	0.30	0.04	11.69	6.73	-4.53	3.74	80.9
	5-1	1.01	-0.18	0.01	-0.38	3.57	-2.07	0.08	-3.88	7.0	0.80	-0.25	0.13	-0.32	0.47	2.65	-2.42	1.17	-3.31	3.51	14.5
EUR	1	-0.41	0.76	0.41	0.21	-2.54	8.23	5.55	2.76	84.6	0.36	0.64	0.41	0.11	-0.81	2.22	7.63	6.47	1.68	-9.71	88.6
	2	0.15	0.41	0.46	0.16	1.74	8.50	11.76	4.06	92.3	0.35	0.37	0.45	0.15	-0.19	3.50	7.35	11.62	3.75	-3.66	91.7
	3	0.47	0.30	0.49	0.06	6.01	6.86	13.76	1.53	92.4	0.40	0.30	0.49	0.08	0.11	4.41	6.54	13.87	2.29	2.31	91.7
	4	0.64	0.33	0.49	-0.05	7.64	6.94	12.85	-1.38	91.7	0.41	0.36	0.49	-0.01	0.27	4.51	7.74	13.75	-0.25	5.84	91.9
	5	1.05	0.52	0.45	-0.20	7.82	6.80	7.32	-3.19	84.7	0.52	0.62	0.44	-0.13	0.56	3.60	8.41	7.77	-2.25	7.55	85.6
	5-1	1.46	-0.24	0.04	-0.41	5.84	-1.68	0.33	-3.49	9.4	0.16	-0.02	0.03	-0.24	1.37	0.66	-0.13	0.27	-2.49	11.13	42.9
UK	5-1	0.90	0.60	-0.62	-0.32	4.02	3.65	-3.99	-3.64	12.0	0.71	0.65	-0.66	-0.34	0.32	2.95	3.83	-4.19	-3.81	2.94	15.3
IRL	5-1	0.40	0.22	-0.27	-0.15	1.00	2.17	-2.51	-2.34	4.5	0.41	-0.08	-0.01	-0.20	0.32	1.01	-0.62	-0.08	-3.37	4.71	16.8
GER	5-1	1.28	-0.85	0.33	0.09	4.36	-7.64	3.15	1.18	27.1	0.53	-0.82	0.37	0.16	0.97	1.91	-6.95	3.68	2.28	8.45	44.2
A	5-1	0.32	0.08	-0.04	-0.06	0.98	0.69	-0.44	-0.95	-0.6	0.05	0.29	-0.12	-0.04	0.33	0.17	2.41	-1.26	-0.75	4.56	8.0
CH	5-1	0.93	-0.06	-0.05	-0.24	3.56	-0.63	-0.48	-3.30	7.4	0.45	-0.08	0.07	-0.18	0.73	1.92	-0.63	0.64	-3.00	9.11	34.2
FR	5-1	1.16	-0.08	-0.23	-0.33	4.19	-0.92	-2.81	-5.00	19.6	0.23	0.00	-0.10	-0.16	0.98	0.90	-0.02	-1.28	-2.77	10.83	46.7
IL	5-1	1.19	-0.52	0.34	-0.10	3.71	-3.97	2.59	-1.33	8.2	1.07	-0.62	0.49	-0.10	0.40	3.37	-4.51	3.50	-1.44	3.98	14.3
GR	5-1	2.17	0.03	0.02	-0.51	4.49	0.40	0.25	-2.64	2.7	2.11	0.04	0.02	-0.50	0.11	4.33	0.49	0.27	-2.56	0.92	2.6
ES	5-1	0.66	-0.12	-0.18	0.05	2.06	-1.01	-1.41	0.65	9.4	0.54	-0.29	0.01	0.03	0.09	1.70	-2.44	0.06	0.42	1.19	11.8
POR	5-1	1.02	-0.12	-0.04	-0.22	2.31	-1.05	-0.46	-1.98	2.2	0.70	-0.12	0.01	-0.19	0.27	1.59	-1.11	0.10	-1.73	3.49	8.3
NL	5-1	1.13	-0.09	-0.07	-0.21	4.11	-0.91	-0.67	-3.37	9.3	0.24	-0.03	0.05	-0.11	0.79	1.02	-0.33	0.54	-2.19	12.06	44.2
BEL	5-1	1.18	-0.18	0.08	-0.11	4.19	-1.60	0.89	-1.45	0.8	0.74	-0.27	0.16	-0.08	0.63	2.78	-2.09	1.74	-1.11	7.83	22.8
SWE	5-1	1.22	-0.13	-0.04	-0.02	3.95	-1.86	-0.48	-0.50	4.0	0.95	-0.16	0.03	-0.03	0.30	3.18	-2.18	0.32	-0.76	4.11	12.6
NOR	5-1	1.06	-0.19	0.07	-0.20	2.67	-1.65	0.67	-2.48	3.9	0.89	-0.12	0.06	-0.17	0.25	2.26	-1.04	0.55	-2.11	3.13	6.8
DK	5-1	1.34	0.05	-0.24	-0.03	4.54	0.37	-2.40	-0.42	3.3	0.82	0.00	-0.15	0.00	0.47	2.87	0.01	-1.54	0.03	7.36	21.5
FN	5-1	1.24	-0.52	0.32	-0.05	3.34	-4.07	2.60	-1.17	8.6	0.48	-0.24	0.15	-0.02	0.57	1.41	-2.07	1.39	-0.62	8.04	29.8

According to Chordia and Shivakumar (2006), for earnings momentum to be the crucial driver of price momentum the former should be robust when controlling for the latter. Hence, we determine the earnings momentum alphas arising from the following four-factor model

$$R_{Lt} - R_{St} = \alpha + \beta(R_{Mt} - R_{Ft}) + \gamma R_{SMBt} + \delta R_{HMLt} + \eta R_{WMLt} + \varepsilon_t, \qquad (5.5)$$

where the original Fama-French model is augmented by the return to the price momentum strategy, R_{WMLt} (winner minus loser). In Table 5.10 we contrast the Fama-French results to those of the above four-factor model for all countries' respective hedge strategies. As before, results for the quintile portfolios according to the U.S. and the European aggregate strategy are also depicted. Again, we note that the additional factor leads to a considerable increase in statistical fit. In fact, the adjusted R^2 of the Fama-French model and the four-factor model almost resemble the figures obtained in the price momentum case. Consistent with Chordia and Shivakumar (2006), the U.S. earnings momentum alpha remains large at 72 basis points with a highly significant t-statistic of 5.14. Given that the European earnings momentum alpha has a t-statistic of 6.76, we suspect that this observation carries over to other countries. Indeed, 13 of 15 original European anomalies remain significant after controlling for price momentum; only Italy and Norway do cease to have significant earnings momentum alphas.

To summarize, among 17 countries we initially find 15 countries exhibiting significant price momentum alphas in a classical Fama-French setting. Among these 15 countries, seven countries follow the explanation offered by Chordia and Shivakumar (2006), i.e., earnings momentum subsumes price momentum. These countries include Germany, Switzerland, France, Spain, Portugal, the Netherlands, and Finland. Among the eight remaining four-factor price momentum anomalies, five countries also have four-factor earnings momentum anomalies (the U.S., the U.K., Belgium, Sweden, and Denmark). Two countries' earnings momentum alphas cease to be significant (Italy and Norway) and Greece exhibits no earnings momentum at all. In summary, we obtain an aggregate European pattern that suggests a translation of Chordia and Shivakumar (2006)'s argument to European equity markets. Thus, it is all the more surprising why we are refuting their rationale for the U.S..

Table 5.10: Time-Series-Regressions of Earnings Momentum Portfolios

The table's left panel gives the results of a regression according to Equation (5.3) using 240 monthly returns ranging from July 1987 to June 2007 followed by the according t-statistics. The right panel gives the results of a regression according to Equation (5.5). We use the country abbreviations introduced in Table 5.1. We give the quintile portfolios 1 (negative earnings revisions) to 5 (positive earnings revisions) together with the long-short portfolio (positive-negative earnings revisions).

		Fama-French Model									*4-Factor Model*										
		α	β	γ	δ	$t(\alpha)$	$t(\beta)$	$t(\gamma)$	$t(\delta)$	Adj. R^2	α	β	γ	δ	ζ	$t(\alpha)$	$t(\beta)$	$t(\gamma)$	$t(\delta)$	$t(\zeta)$	Adj. R^2
USA	1	-0.63	1.00	0.22	0.12	-6.10	27.17	5.30	3.38	92.5	-0.57	0.98	0.23	0.10	-0.05	-5.35	26.13	5.54	2.76	-2.18	92.6
	2	-0.37	0.70	0.28	0.09	-3.88	20.55	7.41	2.91	89.9	-0.30	0.68	0.29	0.07	-0.06	-3.02	19.62	7.80	2.13	-2.95	90.3
	3	-0.18	0.52	0.31	0.07	-1.60	12.85	6.99	1.78	82.2	-0.11	0.49	0.32	0.05	-0.06	-0.97	12.08	7.25	1.20	-2.23	82.5
	4	0.06	0.56	0.33	-0.12	0.46	12.89	6.96	-2.88	82.4	0.09	0.55	0.34	-0.13	-0.03	0.69	12.32	7.01	-3.02	-0.92	82.4
	5	0.22	0.75	0.33	-0.01	1.80	17.50	6.85	-0.16	87.3	0.15	0.77	0.32	0.01	0.06	1.20	17.62	6.65	0.36	2.08	87.5
	5-1	0.85	-0.25	0.11	-0.12	6.15	-5.12	2.01	-2.67	14.5	0.72	-0.21	0.09	-0.08	0.11	5.14	-4.28	1.68	-1.78	3.51	18.5
EUR	1	-0.15	0.72	0.38	0.14	-1.59	12.73	8.56	3.06	92.5	0.10	0.66	0.39	0.08	-0.16	1.08	12.70	9.69	1.82	-6.98	93.7
	2	0.13	0.47	0.49	0.00	1.77	10.84	14.08	0.04	94.3	0.28	0.44	0.49	-0.03	-0.09	3.60	10.45	14.95	-0.98	-4.89	94.8
	3	0.34	0.36	0.48	-0.06	4.57	8.23	13.66	-1.67	92.8	0.42	0.35	0.48	-0.08	-0.04	5.12	7.75	13.90	-2.14	-2.23	92.9
	4	0.57	0.34	0.48	-0.11	6.97	7.03	12.65	-2.98	91.0	0.49	0.36	0.48	-0.09	0.05	5.58	7.39	12.67	-2.44	2.39	91.2
	5	0.89	0.47	0.42	0.03	10.14	9.13	10.25	0.82	90.9	0.74	0.51	0.41	0.07	0.09	8.06	10.00	10.43	1.71	4.21	91.5
	5-1	1.05	-0.25	0.04	-0.10	9.68	-3.94	0.70	-2.07	24.3	0.64	-0.16	0.02	-0.01	0.26	6.76	-3.05	0.40	-0.17	11.13	50.6
UK	5-1	0.80	-0.17	0.06	0.08	6.00	-1.67	0.60	1.56	5.4	0.70	-0.24	0.13	0.12	0.11	5.08	-2.31	1.34	2.20	2.94	8.4
IRL	5-1	1.45	-0.19	0.03	0.02	3.14	-1.24	0.24	0.34	0.2	1.11	-0.14	0.04	0.10	0.39	2.49	-0.93	0.27	1.45	4.71	11.9
GER	5-1	0.87	-0.20	0.07	-0.07	5.80	-3.00	1.22	-1.71	4.8	0.53	0.05	-0.04	-0.09	0.24	3.89	0.75	-0.71	-2.60	8.45	27.0
A	5-1	0.89	-0.35	0.07	-0.08	3.07	-3.28	0.73	-1.48	7.9	0.80	-0.40	0.09	-0.06	0.25	2.88	-3.82	1.05	-1.19	4.56	15.2
CH	5-1	0.81	-0.48	0.22	-0.01	4.37	-4.92	2.55	-0.27	14.8	0.43	-0.32	0.14	0.06	0.37	2.62	-3.79	1.83	1.29	9.11	37.1
FR	5-1	1.00	-0.13	-0.10	-0.18	5.86	-2.18	-1.85	-4.51	21.7	0.58	-0.09	-0.03	-0.06	0.34	4.05	-1.75	-0.75	-1.88	10.83	47.9
IL	5-1	0.42	0.10	-0.22	-0.01	2.03	1.14	-2.40	-0.24	4.4	0.22	0.20	-0.28	0.01	0.16	1.07	2.17	-3.16	0.14	3.98	10.1
GR	5-1	0.45	-0.06	-0.01	-0.13	1.34	-1.10	-0.17	-0.95	3.0	0.42	-0.07	-0.02	-0.10	0.05	1.18	-1.22	-0.25	-0.69	0.92	3.8
ES	5-1	1.03	-0.02	-0.25	0.01	3.65	-0.22	-2.11	0.15	9.5	0.98	0.00	-0.25	0.01	0.07	3.47	-0.02	-2.11	0.12	1.19	9.7
POR	5-1	1.06	0.01	-0.16	-0.08	2.58	0.13	-2.09	-0.80	2.0	0.94	0.04	-0.16	-0.07	0.25	2.26	0.35	-2.11	-0.65	3.49	8.9
NL	5-1	1.08	0.03	-0.23	-0.14	4.89	0.31	-2.47	-2.80	13.9	0.55	0.04	-0.16	-0.03	0.49	3.05	0.45	-2.26	-0.78	12.06	47.1
BEL	5-1	0.88	-0.17	0.06	-0.04	4.19	-1.67	0.80	-0.68	0.7	0.45	-0.05	-0.01	0.00	0.34	2.29	-0.50	-0.08	-0.09	7.83	21.3
SWE	5-1	0.93	-0.21	0.08	-0.01	3.55	-3.32	1.02	-0.26	6.5	0.65	-0.16	0.07	0.00	0.23	2.48	-2.56	0.90	-0.05	4.11	12.5
NOR	5-1	0.71	-0.18	-0.03	-0.07	2.16	-1.88	-0.35	-1.01	6.6	0.53	-0.15	-0.04	-0.04	0.17	1.62	-1.62	-0.45	-0.55	3.13	10.1
DK	5-1	1.23	0.05	-0.17	-0.05	4.32	0.37	-1.70	-0.87	1.3	0.66	0.04	-0.08	-0.04	0.41	2.47	0.32	-0.85	-0.80	7.36	19.8
FN	5-1	1.40	-0.48	0.28	-0.05	4.44	-4.39	2.71	-1.30	10.1	0.82	-0.27	0.16	-0.02	0.41	2.88	-2.74	1.73	-0.81	8.04	31.4

To uncover whether this reasoning may be confined to special circumstances, we investigate the time series of price momentum alphas arising from a trailing regression. First, we consider price momentum and contrast the respective Fama-French alpha (dashed line) and the four-factor alpha (solid line) in the upper graphs of Figure 5.3. For the U.S., we see that the large Fama-French alpha is substantially reduced when additionally controlling for earnings momentum. However, by the end of 1999, which coincides with the end of the sample period in Chordia and Shivakumar (2006), this relation breaks down for some years. Obviously, price and earnings momentum have decoupled following the burst of the tech bubble. This reasoning supports the general view that price momentum typically will be a result of investors' underreaction to fundamental news, while the market frenzy at the end of the nineties is more likely the result from overreaction. This observation suggests that U.S. investors will most likely have put less weight on earnings information following several accounting scandals at the beginning of the century. On the other hand, the European Fama-French price momentum alpha is literally neutralized by the earnings momentum factor for the whole sample period. Hence, while earnings momentum is a crucial driver of price momentum there seem to be other forces at work, too.

5.6 Origins of Momentum: Risk or Behavioral Bias?

The results of the previous section essentially suggest that any momentum rationale will be closely linked to the drivers of earnings momentum. In further rationalizing the momentum anomaly, we consider the following ideas. First, we mimic Chordia and Shivakumar (2006) in examining the link between momentum and the macroeconomy. Second, we will analyze the interaction of momentum with measures of information uncertainty. Third, we will investigate the role of liquidity risk in momentum profits.

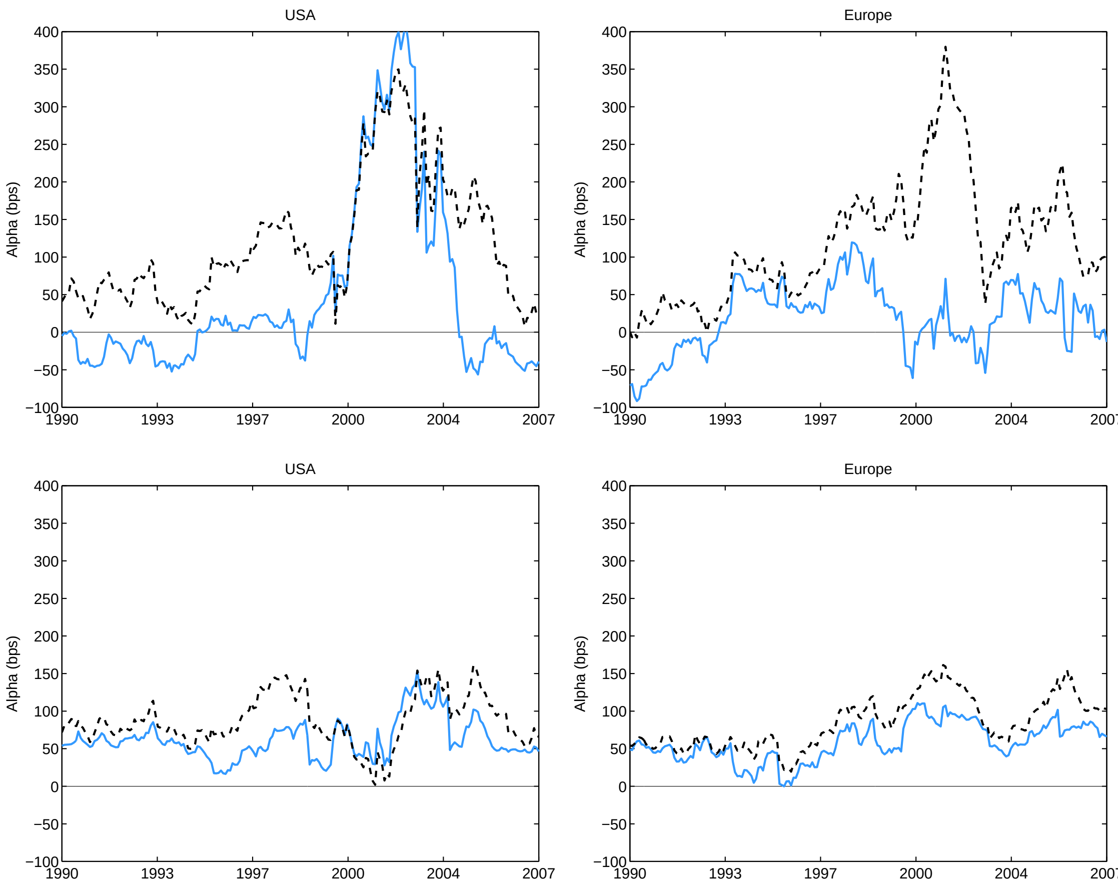
5.6.1 Momentum and the Macroeconomy

It may well be that momentum is closely related to the macroeconomy since momentum may simply reflect future macroeconomic activity or the mispricing of certain macroeconomic variables. To test the respective relation, we follow Liew and Vassalou (2000) and Chordia and Shivakumar (2006) in regressing future GDP growth on lagged values of the Fama-French factors and one of the two momentum factors.

Table 5.11 gives the results of a regression of 12-month ahead growth in real GDP on 12-month compounded momentum, either price momentum WML or earnings

Figure 5.3: Momentum: Fama-French versus Four-Factor Alphas

In the upper graphs we plot trailing price momentum alphas arising from equations (5.3) and (5.4) using 36-months windows, thus results cover July 1990 to June 2007. Likewise, the lower graphs give trailing earnings momentum alphas arising from equations (5.3) and (5.5). The dashed line gives the Fama-French alpha and the solid line is the respective four-factor alpha.



momentum PMN, and Fama-French factors MKT, SMB, and HML. GDP growth is measured as the change in the log of GDP. Given that GDP is available on a quarterly basis, the regressions are also on a quarterly basis. Since the regressions rely on overlapping data, the reported t-statistics are based on Newey-West standard errors, see Newey and West (1987). The sample period is from July 1987 to June 2007.

The following results can be inferred from Table 5.11. First, we recover the market factor—if significant— to be a leading indicator of future economic growth in some of the countries, i.e., both are positively related as indicated by the positive coefficient estimates. Second, while Liew and Vassalou (2000) report SMB and HML to also be positively related to future GDP growth in major equity markets until the middle of the nineties, we find a negative relation in many countries. That is,

Table 5.11: Momentum and the Macroeconomy

The Table gives the results of a regression of 12-month ahead growth in real GDP on 12-month compounded momentum MOM and Fama-French factors MKT, SMB, and HML. GDP growth is measured as the change in the log of GDP and given that GDP is available on a quarterly basis the regressions are also on a quarterly basis. The regressions' intercept is denoted by ICT. Since the regressions rely on overlapping data the reported t-statistics are based on Newey-West standard errors. The upper Panel refers to price momentum and the lower panel refers to earnings momentum. We use the country abbreviations introduced in Table 5.1. The sample period is from July 1987 to June 2007.

	Coefficients					*t-statistics*					
	ICT	MOM	MKT	SMB	HML	ICT	MOM	MKT	SMB	HML	Adj. R^2
Panel A: Price Momentum											
USA	0.037	-0.045	-0.014	0.020	-0.036	7.46	-1.32	-0.68	0.71	-2.31	11.0
EUR	0.014	0.023	0.051	-0.032	-0.030	2.91	1.86	1.38	-0.84	-1.31	45.4
UK	0.019	0.031	0.003	0.023	0.021	2.97	2.33	0.14	0.70	0.71	14.3
IRL	0.071	-0.034	0.062	-0.082	-0.030	11.38	-2.46	1.58	-1.71	-1.84	21.5
GER	0.013	0.000	0.041	-0.025	0.003	2.64	0.00	0.78	-0.56	0.19	10.0
A	0.021	-0.005	-0.002	0.019	0.005	5.67	-0.75	-0.07	0.90	0.33	13.7
CH	0.014	-0.003	0.103	-0.076	-0.014	3.24	-0.32	3.43	-3.32	-1.03	25.0
FR	0.018	0.006	-0.013	0.033	-0.008	2.57	0.40	-0.36	0.98	-0.94	10.5
IL	0.013	0.010	0.098	-0.084	0.009	2.26	0.66	2.89	-2.42	0.91	18.0
GR	0.047	-0.009	0.011	-0.010	-0.026	24.56	-2.33	0.75	-0.82	-1.91	15.5
ES	0.070	-0.017	-0.009	0.019	0.015	16.81	-1.08	-1.12	1.36	0.96	11.3
POR	0.024	-0.019	-0.022	0.037	-0.024	1.72	-1.01	-0.84	3.78	-0.65	25.5
NL	0.021	0.023	0.085	-0.062	0.008	4.90	1.37	2.32	-2.19	0.50	30.4
BEL	0.010	0.026	0.036	-0.010	0.040	3.26	4.43	1.26	-0.31	1.85	52.0
SWE	0.029	0.006	-0.014	0.034	-0.001	7.32	0.35	-0.90	1.46	-0.13	8.6
NOR	0.030	-0.023	0.039	-0.045	-0.006	6.50	-1.47	1.60	-1.72	-0.39	21.7
DK	0.025	-0.018	0.017	-0.009	-0.006	3.23	-0.89	0.49	-0.38	-0.36	-1.1
FN	0.018	0.035	-0.021	0.064	-0.029	1.78	1.09	-1.27	4.51	-1.84	39.0
Panel B: Earnings Momentum											
USA	0.022	0.086	0.030	-0.029	-0.019	4.48	2.75	1.31	-0.93	-1.26	27.1
EUR	0.007	0.083	0.076	-0.055	-0.027	1.30	2.78	2.95	-1.72	-1.36	51.1
UK	0.022	0.010	0.009	0.013	0.007	2.84	0.36	0.34	0.28	0.22	6.6
IRL	0.058	0.003	0.075	-0.082	-0.002	10.62	0.17	1.85	-1.84	-0.11	0.2
GER	0.009	0.031	0.045	-0.029	0.007	1.78	1.25	1.14	-0.73	0.52	15.8
A	0.024	-0.021	-0.013	0.030	0.004	11.07	-1.66	-0.57	1.93	0.29	30.2
CH	0.012	0.015	0.119	-0.086	-0.021	3.93	1.06	3.19	-3.21	-1.30	26.2
FR	0.018	0.016	-0.015	0.036	-0.007	2.00	0.63	-0.37	0.96	-0.85	11.4
IL	0.014	0.012	0.104	-0.091	0.010	2.35	0.45	2.61	-2.28	1.04	17.9
GR	0.046	-0.012	0.004	-0.002	-0.028	43.25	-1.54	0.28	-0.19	-4.34	31.1
ES	0.069	0.008	-0.019	0.029	0.016	15.64	0.55	-1.85	1.78	0.98	7.6
POR	0.009	0.039	-0.017	0.029	0.020	0.87	2.71	-0.82	1.97	0.52	36.0
NL	0.023	0.003	0.102	-0.072	0.007	5.10	0.14	2.63	-2.14	0.38	22.5
BEL	0.013	0.024	0.037	-0.012	0.042	2.96	2.34	1.15	-0.36	1.70	32.1
SWE	0.026	0.020	-0.014	0.040	-0.002	5.25	1.42	-0.90	1.63	-0.26	16.3
NOR	0.028	-0.024	0.048	-0.061	0.010	7.84	-1.53	2.27	-2.78	0.66	20.4
DK	0.023	-0.003	0.014	-0.007	-0.010	3.09	-0.19	0.45	-0.32	-0.68	-3.7
FN	0.021	0.009	-0.034	0.078	-0.026	1.99	0.24	-2.09	4.19	-2.20	33.6

small cap or value stocks suffer prior to periods of economic growth, whereas they thrive before an economic slowdown. Third, the link between earnings momentum and macroeconomy appears to be strongest in the U.S. and the European aggregate. Given a positive relation instead of a negative one suggests that earnings momentum is a proxy for a macroeconomic risk factor. However, besides the U.S. and the Europe aggregate, we can only obtain two further countries in which earnings momentum significantly predicts GDP growth: Portugal and Belgium exhibit a positive relation. Hence, there appears to be no definite pattern in linking earnings momentum to the macroeconomy, an observation that carries over to the regression results obtained using the price momentum factor.

While our findings sharply contrast with the U.S. result of Chordia and Shivakumar (2006), who detect a negative relation but for a different time period, it is by and large affirmative of the international study of Liew and Vassalou (2000). They fail to find a link between WML and GDP growth. Given the strong link between price and earnings momentum documented in this paper, we are thus bound to uncover a similar result for PMN. Also, using alternative measures of the macroeconomy like industrial production growth or consumption growth reveals (unreported) results that are qualitatively similar to the ones for GDP growth.

Furthermore, our evidence aligns with the study of Griffin, Ji, and Martin (2003) who also fail to establish a link between price momentum and macroeconomic risk factors in many countries. However, one may argue that momentum may be more of a common factor phenomenon when focussing on bigger companies. For instance, Scowcroft and Sefton (2005) argue that the finding of industry momentum driving price momentum is confined to large cap universes. Since we are dealing with a very comprehensive sample we may thus be prone to refute any common factor effects in momentum. However, Kang and Li (2005) show that traditional approaches of separating common from stock-specific factors are flawed in that they have a stock-specific component implicit in the common factor component. This problem is remedied within their model and their empirical results suggest that the stock-specific component is probably the only source of U.S. momentum profits. To conclude, failing to find a definite relation between momentum and the macroeconomy may suggest that momentum is rather due to a behavioral bias, an idea we will explore in the following.

5.6.2 Momentum and Information Uncertainty

In this section, we will analyze the interaction of momentum and information uncertainty. The theoretical model of Hong and Stein (1999) posits that firm-specific information only gradually spreads across investors resulting in underreaction and, as a consequence, short-term return continuation. If momentum is due to investors' underreaction to fundamental news, the respective price drift should be higher in more opaque information environments for which information diffusion is slowest. In fact, Hong, Lim, and Stein (2000) find empirical support for their theory by demonstrating that U.S. momentum strategies are more effective in companies of small size or in companies with low analyst coverage. Besides these two metrics, Zhang (2006) recently provides evidence that the U.S. price momentum strategy is also more effective when limited to high uncertainty stocks as measured by firm age, dispersion in analysts' earnings forecasts, stock volatility, and cash flow volatility. Especially, the dispersion in analysts' earnings forecasts has been used in prior studies to proxy for differences in opinion, see Diether, Malloy, and Scherbina (2002). For instance, this heterogeneity in beliefs is a necessary condition for price drift in the model of Banerjee, Kaniel, and Kremer (2008), a link that is empirically corroborated for the U.S. by Verardo (2008).

Of course, establishing a link between international momentum and information uncertainty would further substantiate the momentum rationale of investors underreacting to fundamental news. Hence, we will examine price and earnings momentum profits for different degrees of information uncertainty. We consider four measures to monthly proxy for information uncertainty: Analyst coverage, size, total stock volatility, and idiosyncratic volatility. Total stock volatility is estimated using the last three year's monthly stock returns, and idiosyncratic volatility arises from a standard Fama-French regression that also uses the last three year's monthly stock returns.

Table 5.12 gives the results for the price momentum strategy in the upper panel A. In particular, we first sort stocks into five quintiles based on past returns. For each quintile the stocks are further sorted into three terciles based on one of the four information uncertainty proxies. Obviously, this procedure requires a sufficient number of companies in a given country to deliver meaningful results and we therefore exclude the seven smallest countries from the analysis, i.e., Austria, Belgium, Finland, Greece, Ireland, Norway, and Portugal.

Our findings are as follows. First, we confirm the empirical evidence for the U.S.: Price momentum is indeed more pronounced for stocks with low analyst coverage, smaller size or higher volatility, be it total or idiosyncratic volatility. Second, the latter findings do not only translate to the European momentum strategy, but also to most of the European country strategies. In fact, only Denmark does refute the underreaction rationale. Third, while the earnings momentum results are quite similar among the major equity markets, we note that the results for some smaller countries are somewhat muted.

Table 5.12: Momentum and Information Uncertainty

The table gives return differentials of the price and earnings momentum hedge strategies by terciles of different information uncertainty metrics. In Panel A we first sort stocks into five quintiles based on past returns. For each quintile the stocks are further sorted into three terciles based on analyst coverage, size, total stock volatility and idiosyncratic volatility. Below the return differentials we give t-statistics. The last two rows collect the number of countries that exhibit the highest return differential among the respective terciles and the terciles mean ranking in terms of returns. Panel B gives analogous results for earnings momentum.

Country	*Analyst Coverage*			*Size*			*Volatility*			*Idiosyncratic*		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Panel A: Price Momentum												
USA	1.38	1.04	0.87	1.53	0.91	0.48	0.29	1.02	1.28	0.97	0.98	1.41
	5.77	4.15	2.69	6.87	3.24	1.37	1.69	3.93	4.62	3.01	3.79	5.49
Europe	1.66	1.69	1.16	2.10	1.41	1.04	1.07	1.47	1.60	1.47	1.22	1.71
	6.77	7.21	4.83	7.54	5.46	3.87	6.15	6.39	6.25	5.50	5.23	6.74
UK	1.50	1.44	0.67	1.56	1.25	0.50	0.77	0.99	1.42	1.12	1.24	1.31
	4.83	4.55	2.02	4.95	4.15	1.57	3.86	3.39	4.73	3.90	4.33	4.49
Germany	0.98	1.14	1.04	1.48	1.03	0.78	0.75	0.94	1.11	1.29	0.99	1.36
	3.40	4.10	3.32	4.46	3.01	2.24	2.86	3.54	3.45	3.49	3.06	4.39
Switzerland	1.42	1.60	1.21	1.41	1.20	0.77	1.83	1.33	1.46	1.76	1.00	1.53
	4.38	5.36	4.18	4.14	3.67	2.37	5.98	4.63	4.90	5.25	3.79	4.95
France	1.21	1.24	0.82	1.75	1.32	0.46	1.32	1.16	1.21	1.45	1.06	1.51
	3.98	3.94	2.72	5.53	3.97	1.38	5.87	4.17	3.80	4.21	3.20	5.11
Italy	1.13	1.63	0.68	1.60	0.93	0.85	0.10	0.96	1.21	1.24	0.97	1.21
	2.55	3.67	1.74	3.62	1.92	1.84	0.25	2.50	2.86	2.78	2.27	2.94
Spain	0.90	0.51	0.13	1.45	0.79	-0.04	0.94	0.69	0.62	0.58	0.35	0.64
	1.90	1.32	0.29	2.33	1.96	-0.11	2.25	2.11	1.40	1.52	0.97	1.64
Netherlands	1.24	0.95	0.82	1.08	1.00	0.57	0.90	0.77	1.13	1.00	0.72	1.22
	3.79	2.89	2.38	3.37	2.86	1.46	2.83	2.73	3.30	2.91	2.43	3.77
Sweden	0.93	1.30	0.73	0.83	1.79	0.62	0.98	0.91	1.10	1.32	0.64	1.02
	1.96	3.38	1.92	1.79	3.77	1.44	2.97	2.27	3.02	3.00	1.62	2.52
Denmark	0.60	0.97	1.01	0.42	1.66	1.29	1.55	0.60	0.91	1.44	0.54	1.16
	1.56	3.41	3.48	1.07	3.66	3.47	4.24	2.10	3.02	3.51	1.99	3.39
# max	4	6	1	9	2	0	4	0	7	4	0	7
ranking	1.82	1.45	2.73	1.27	1.82	2.91	2.09	2.45	1.45	1.82	2.82	1.36
Panel B: Earnings Momentum												
USA	1.04	0.60	0.16	1.08	0.58	0.24	0.48	0.52	0.68	0.50	0.63	0.70
	7.41	3.77	0.75	7.02	3.55	1.22	3.99	3.87	4.62	3.56	4.28	4.26
Europe	0.92	1.00	0.58	1.20	0.71	0.70	0.68	0.68	0.88	0.87	0.89	0.89
	8.42	7.35	3.48	8.09	6.06	4.42	6.51	6.73	7.07	7.62	7.97	5.99
UK	1.22	1.00	0.29	1.50	0.83	0.35	0.61	0.59	0.93	0.62	0.89	1.00
	5.71	4.66	1.52	6.50	4.16	1.70	3.80	3.28	5.05	3.99	4.73	4.48
Germany	0.83	0.92	0.55	1.01	0.83	0.24	0.76	0.76	0.70	0.79	0.72	0.73
	3.09	3.96	2.16	3.50	3.71	1.26	4.02	4.31	3.37	4.06	3.77	2.94
Switzerland	0.57	0.80	0.69	0.95	0.46	0.66	0.45	0.31	0.76	0.65	0.60	0.71
	1.95	2.86	2.35	3.09	1.83	2.36	2.20	1.30	2.98	2.83	2.51	2.23
France	0.45	0.99	0.60	0.60	0.78	0.66	0.92	0.67	0.67	0.86	0.89	0.73
	1.86	3.39	2.16	1.92	3.17	2.60	4.48	3.04	3.04	4.23	3.84	2.71
Italy	0.03	0.66	0.52	0.03	0.52	0.33	-0.13	0.57	0.03	0.28	0.84	0.45
	0.11	1.85	1.69	0.09	1.53	1.01	-0.54	2.02	0.11	0.96	2.89	1.19
Spain	0.73	0.71	1.00	1.64	0.16	0.75	0.65	0.88	1.23	1.12	0.83	0.44
	2.11	1.86	1.84	2.42	0.47	2.31	2.75	2.60	2.72	3.43	2.16	1.19
Netherlands	1.26	1.17	0.04	1.39	1.08	0.06	0.97	0.60	0.52	1.01	0.82	1.11
	4.47	3.50	0.13	4.43	3.45	0.14	3.41	2.13	1.82	4.02	2.89	3.21
Sweden	1.01	1.61	0.51	0.93	1.75	-0.06	1.02	0.90	0.93	0.42	0.88	1.20
	2.89	4.59	1.24	2.92	4.63	-0.15	3.60	2.69	3.07	1.33	2.46	3.08
Denmark	1.22	0.94	0.93	1.32	1.13	0.74	2.19	0.67	1.12	1.57	1.34	0.89
	2.80	1.88	2.41	1.61	3.33	2.31	1.91	2.06	3.36	2.81	4.93	2.29
# max	4	6	1	8	3	0	5	2	5	3	3	6
ranking	1.91	1.55	2.55	1.45	1.91	2.64	1.82	2.18	1.73	2.18	2.00	1.73

Thus, having gathered substantial support for the underreaction theory, one may wonder as to why the momentum anomaly is not arbitraged away. For the U.S., recent research contends that high arbitrage costs prevent rational investors from exploiting the momentum anomaly, see Arena, Haggard, and Yan (2008) for price momentum and Mendenhall (2004) for post-earnings announcement drift. Presumably, the cost of short-selling small stocks is not offset by the expected momentum profits. In fact, a stock's idiosyncratic volatility is a common proxy for arbitrage costs. The fact that we find momentum to be most pronounced in stocks with high idiosyncratic volatility additionally provides a persuasive explanation for the persistence of the momentum effect.

5.6.3 Momentum and Liquidity

In further elaborating on the above argument we next examine the role of liquidity when implementing momentum strategies. Lesmond, Schill, and Zhou (2004) and Korajczyk and Sadka (2004) evidence that exploiting U.S. price momentum is costly, in fact, trading costs appear to erode all of the potential profits rendering the momentum arbitrage opportunity an illusion. The trading costs basically derive from frequent trading in mostly illiquid stocks. Consequently, Sadka (2006) documents a close relation between liquidity risk and U.S. momentum strategies. Moreover, Liu (2006)'s liquidity-augmented two-factor asset pricing model almost completely subsumes the U.S. price momentum alpha. Hence, we expect liquidity to also play a crucial role in inhibiting profitable execution of the European momentum strategies.

To operationalize this conjecture we will analyze the profitability of the momentum strategies when restricting to winner and loser stocks characterized by different degrees of liquidity. Liu (2006) aptly describes liquidity "as the ability to trade large quantities *quickly* at low cost with little price impact". To account for the according distinct dimensions of liquidity we compute different metrics. A stock's dollar volume or its turnover allow to capture the trading quantity dimension. As for the price impact dimension we resort to the *ILLIQ* measure of Amihud (2002) which is the absolute daily return over the associated dollar volume. To obtain an aggregate monthly value of *ILLIQ* we simply compute its mean over the corresponding daily values. The fourth measure is the one introduced by Liu (2006) which has been designed to capture multiple dimensions of liquidity, such as trading speed and trading quantity. Its definition is as follows:

$$\text{Liu Measure} = \text{Number of No-Trading Days over the prior 12 months} + \frac{1/\text{Turnover}}{1,000,000}$$

where turnover is the average daily turnover over the prior 12 months. This measure addresses the trading speed dimension of liquidity since it very well captures lock-in-risk, i.e., the danger of being locked in a certain position that cannot be sold.[3]

Table 5.13 displays the profitability of momentum strategies restricted to winner and loser stocks characterized by different degrees of liquidity. In particular, we first sort stocks into five quintiles based on past returns or earnings revisions. For each quintile the stocks are further sorted into three terciles based on one of the four liquidity measures. Again, we exclude the seven smallest countries from the analysis, i.e., Austria, Belgium, Finland, Greece, Ireland, Norway, and Portugal. Panel A of Table 5.13 gives the results for the price momentum strategy. Across most countries and liquidity metrics the general pattern is that the least momentum profits occur for the most liquid stocks and that profitability is increasing with illiquidty. For instance, U.S. price momentum for stocks with the lowest *ILLIQ* values is only significant at the 10%-level and price momentum for high volume stocks is also significantly smaller than the result obtaining for the whole sample.

However, this pattern of momentum profitability decreasing with liquidity is less pronounced for the aggregate European strategy. The according hedge returns still amount to at least 120 basis points per month with t-statistics well above 4—suggesting that momentum may be less costly to implement in Europe than in the U.S.. This observation especially seems to derive from the U.K., Germany and Switzerland in which price momentum is rather strong among more liquid securities. On the other hand, France, Spain and the Netherlands do not exhibit sustainable momentum in the most liquid securities. However, Italy, Sweden and Denmark even reverse the expected outcome by exhibiting no momentum in the least liquid securities.

[3] Note that while the first three measures only take into account the stocks' liquidity over the precedent month the Liu measure hinges on data of the preceding year.

Table 5.13: Momentum and Liquidity

The table gives return differentials of the price and earnings momentum hedge strategies by terciles of different liquidity metrics. In Panel A we first sort stocks into five quintiles based on past returns. For each quintile the stocks are further sorted into three terciles based on dollar volume, share turnover, the ILLIQ measure of Amihud, and Liu's measure. Below the return differentials we give t-statistics. The last two rows collect the number of countries that exhibit the highest return differential among the respective terciles and the terciles mean ranking in terms of returns. Panel B gives analogous results for earnings momentum.

Country	*Dollar Volume*			*Share Turnover*			*ILLIQ*			*Liu Measure*		
	High	Mid	Low	High	Mid	Low	Low	Mid	High	Low	Mid	High
Panel A: Price Momentum												
USA	0.72	0.92	1.15	1.08	0.70	0.76	0.63	0.97	1.29	0.94	0.56	1.34
	2.06	3.42	5.61	3.55	2.80	3.57	1.81	3.56	5.66	3.21	2.08	5.96
Europe	1.25	1.55	1.36	1.63	1.18	1.19	1.23	1.55	1.39	1.41	1.33	1.49
	4.64	6.24	6.87	6.00	5.14	6.02	4.70	6.01	6.62	5.18	5.40	7.47
UK	0.91	1.19	1.29	1.18	1.00	1.19	0.88	1.16	1.33	1.02	1.02	1.29
	3.12	4.23	4.59	4.15	3.66	4.22	3.04	3.98	4.85	3.70	3.60	4.58
Germany	1.14	1.15	1.06	1.21	1.03	0.87	1.08	1.07	1.16	1.07	1.17	1.11
	3.33	3.82	4.29	3.74	3.61	3.79	3.50	3.16	4.17	3.23	4.04	4.51
Switzerland	1.51	0.85	1.15	1.34	0.97	1.17	1.33	1.01	1.18	1.29	1.17	1.19
	4.20	2.75	3.82	3.78	3.29	4.56	3.79	3.07	3.99	3.78	3.67	4.11
France	0.66	1.36	1.22	1.08	1.25	0.95	0.71	1.38	1.14	1.06	1.22	1.06
	1.94	4.52	4.42	3.30	4.25	3.50	2.09	4.37	4.29	3.26	3.98	3.71
Italy	1.39	1.30	0.65	1.16	0.82	0.61	1.16	1.17	0.88	1.34	1.34	0.72
	3.18	3.09	1.65	2.56	2.15	1.57	2.79	2.76	2.29	2.80	3.84	1.53
Spain	0.35	0.33	0.98	0.78	0.54	0.16	0.23	0.34	0.93	0.69	0.08	0.51
	0.87	0.87	1.80	1.87	1.31	0.43	0.54	0.86	2.02	1.72	0.21	1.09
Netherlands	0.67	0.79	1.24	0.75	0.89	1.15	0.73	0.95	0.89	0.80	1.23	0.60
	1.69	2.14	3.70	1.98	2.85	3.43	1.80	2.78	2.87	2.09	3.52	1.97
Sweden	1.02	1.52	0.27	1.47	0.92	-0.18	1.10	0.92	0.40	1.25	0.84	0.58
	2.50	3.25	0.58	3.42	2.26	-0.45	2.63	2.06	0.94	2.94	2.03	1.44
Denmark	1.16	0.95	0.92	1.08	0.76	1.34	1.32	0.97	0.72	1.26	1.18	0.79
	3.57	3.06	2.42	3.12	2.44	3.61	4.14	3.14	2.09	3.60	3.71	1.97
# max	3	4	4	7	1	3	3	4	5	5	4	3
ranking	2.18	1.82	2.00	1.45	2.36	2.18	2.27	1.82	1.82	1.64	2.00	2.09
Panel B: Earnings Momentum												
USA	0.27	0.45	0.97	0.31	0.57	0.79	0.23	0.54	1.01	0.4	0.42	1.02
	1.38	2.62	6.96	1.55	3.66	5.94	1.19	3.16	6.97	2.11	2.58	8.18
Europe	0.77	0.86	0.90	0.91	0.74	0.91	0.79	0.80	0.94	0.89	0.83	0.95
	4.85	6.84	8.17	6.14	5.56	8.59	5.40	6.27	8.20	5.67	6.73	9.68
UK	0.89	0.87	1.00	1.07	0.65	0.97	0.88	0.98	0.92	0.88	0.78	1.03
	5.11	5.18	5.51	6.38	4.08	5.14	5.42	5.70	5.04	5.38	4.70	5.61
Germany	0.56	0.83	0.98	0.80	0.68	0.91	0.54	0.80	0.82	0.60	0.79	0.80
	2.78	4.76	4.05	3.75	4.07	4.57	2.87	4.52	3.39	3.11	4.76	3.25
Switzerland	0.71	0.48	0.64	0.78	0.43	0.66	0.85	0.23	0.54	0.72	0.47	0.73
	2.42	1.76	2.38	2.59	1.67	2.65	2.95	0.75	2.07	2.41	1.82	2.76
France	0.38	0.93	0.49	0.65	0.78	0.73	0.69	0.74	0.53	0.70	1.01	0.39
	1.32	4.30	2.11	2.48	3.42	3.32	2.69	3.16	2.38	2.58	4.83	1.75
Italy	0.86	0.25	-0.05	0.93	0.07	0.13	0.80	0.21	-0.08	0.62	0.13	0.13
	3.09	0.87	-0.15	2.62	0.25	0.46	3.02	0.76	-0.24	2.02	0.47	0.45
Spain	1.00	0.88	0.92	1.11	0.78	0.88	0.85	0.89	1.05	0.85	0.90	0.99
	1.96	2.05	2.34	2.37	1.91	2.38	2.06	2.17	2.70	1.88	2.37	2.47
Netherlands	0.40	0.77	1.37	0.42	0.50	1.42	0.56	1.07	0.99	0.57	0.97	1.04
	0.99	2.15	5.22	1.23	1.68	4.89	1.35	3.35	3.69	1.64	2.69	4.03
Sweden	0.39	0.65	0.97	0.64	0.94	0.84	0.54	0.63	1.15	0.59	1.01	0.87
	0.91	1.92	2.60	1.56	2.43	2.40	1.28	1.87	3.12	1.33	3.34	2.33
Denmark	0.97	1.66	2.36	1.15	1.25	2.26	1.25	1.46	1.85	1.43	1.65	1.77
	2.13	3.76	2.58	2.62	2.26	2.75	2.56	2.91	2.84	2.20	4.07	2.47
# max	3	1	7	5	2	5	2	3	6	1	2	8
ranking	2.36	2.18	1.45	2.00	2.36	1.55	2.45	1.91	1.64	2.45	2.09	1.36

Interestingly, when using the metric share turnover the direction of the liquidity-momentum profitability relationship is sometimes reversed. For instance, judging by share turnover both the U.S. and European aggregate price momentum strategy are most profitable in the most liquid securities. This puzzling result is in line with Hou, Peng, and Xiong (2006) who argue that trading volume as measured by turnover is a proxy for investor attention. When price momentum is mainly an overreaction-driven phenomenon it should be relatively stronger among high turnover stocks. Vice versa, earnings momentum that is likely to be more related to underreaction should be relatively stronger among low turnover stocks since investor attention is presumably lower. Considering Panel B of Table 5.13 we do in fact recover this result for U.S. earnings momentum—regardless of the liquidity measure. The finding is most pronounced for the *ILLIQ* measure for which we obtain an insignificant monthly return spread of 23 basis points. This result complements the findings of Chordia, Goyal, Sadka, Sadka, and Shivakumar (2007) who show the post-earnings announcement drift to be equally useless among illiquid stocks as measured by *ILLIQ*.

For Europe, the results for the aggregate earnings momentum are quite different; in fact, across all liquidity measures the strategy earns at least 74 basis points with t-statistics in excess of 5. However, the country-level results are more in line with the persuasive U.S. story. For example, Germany, France, the Netherlands, Sweden and Denmark exhibit considerably less earnings momentum for highly liquid stocks. All in all, our results suggest that liquidity appears to be a more severe impediment to implementing earnings momentum strategies as opposed to price momentum strategies. Corroborating the rationale of Hou, Peng, and Xiong (2006) we also find the highest U.S. price momentum among high turnover stocks, however, all of the remaining liquidity measures do not support this finding. Still, we think that overreaction may play a role in driving the differences between the price and earnings momentum findings.

Chapter 6

The Dispersion Effect

Earnings estimates of financial analysts serve as a timely measure for assessing a company's current value. Comprising the expertise of different analysts the Institutional Brokers' Estimate System (I/B/E/S) provides a consensus estimate, which basically is a mean value of all available earnings forecasts for a given company. To judge the credibility of the earnings signal, one can resort to additional information embedded in the distribution of analysts' earnings forecasts. Especially, the latter's second moment is a natural candidate to capture the dispersion of analysts' earnings forecasts. Intuitively, one may well expect companies with higher dispersion in analysts' earnings forecast to earn higher returns, thus compensating investors for bearing uncertain earnings prospects. However, empirical evidence for the U.S. is at odds with dispersion being a priced risk factor. Even more so, Diether, Malloy, and Scherbina (2002) document that low dispersion stocks are significantly outperforming high dispersion stocks.

In rationalizing this striking result Diether, Malloy, and Scherbina (2002) contend that dispersion may thus not be viewed as a risk factor, but rather as a metric for differences of opinion. Invoking an argument of Miller (1977), they suggest that prices tend to reflect the view of the optimistic investors whenever there is disagreement about a stock's value since the pessimistic investors' views are often not revealed due to short-sale constraints. In fact, Boehme, Danielsen, and Sorescu (2006) show that the dispersion effect is most prominent among short-sale constrained firms. Of course, the high dispersion stocks' prices are bound to fall once the uncertainty is resolved.

We wonder whether this dispersion effect is common to various markets or whether it is unique to the U.S.. In that regard, we provide original evidence of a dispersion effect in some European markets.

6.1 Data

6.1.1 Sample Selection

The sample that we use is almost identical to the one employed for our study of the momentum effect in Chapter 5. The sole difference lies in the exclusion of Ireland for which we lack sufficient dispersion observations. However, for this chapter's exposition to be self-contained we again describe the sample selection process: We use a comprehensive sample of companies domiciled in 16 equity markets, 15 European markets and the U.S., covering the period from 1987 to 2007. All data has been gathered from Datastream including I/B/E/S earnings revisions data.

Table 6.1 contains descriptive characteristics on the sample countries classified by region. We collect companies for each country by merging the live and dead research lists provided by Datastream on July 2nd, 2007 and thereby obtain a total number of 65,738 companies. To arrive at our final sample, we have pruned the initial country research lists as follows. First, we adjust each country list for secondary issues and cross-country listings to prevent us from double-counting. In particular, we extract 30,454 companies. Hence, one half of the initial list does refer to major listings. Second, we screen for non-equity issues, i.e., we exclude investment trusts, ADRs, and the like. Third, we also exclude OTC stocks and stocks that are only listed on regional exchanges. After these two screens 16,568 companies remain. We further exclude those companies having market capitalization below 10 million USD, which leaves us with a final sample of 12,998 companies. Almost one half are U.S. companies and the biggest five markets comprise around 80%. To avoid survivorship bias, the sample includes 4,524 "dead" companies, i.e., one third of the whole sample, ranging from 16.9% for Greece to 52.2% for Portugal. The label "dead" applies to companies in extreme distress and to those being merged, delisted, or converted.

Since we aim to investigate the dispersion effect, we additionally check the coverage of return and earnings revisions data. Unsurprisingly, the coverage for return data is close to 100% in each country, on average 98.4% of the companies do exhibit at least one return observation over the course of the sample period. On the other hand, the earnings estimate figures are more fragmentary. However, the average coverage still amounts to 75.5% spanning a range from 62.6% (Belgium) to 94.1% (Spain). Note that our sample contains a certain amount of penny stocks that will not be included in the investment strategies. We do not discard them right away, since being a penny stock is not a static firm characteristic. In particular, we do not invest in companies with stock price below $5 at the beginning of a given month.

Table 6.1: Country Overview

The table contains descriptive information on the companies that have been domestically traded in the sample period (1987-2007). For further reference we may use abbreviated country codes (Abb.). The screening of country lists depicts the evolution of the countries' samples. First, we give the *total* size of the country lists followed by the number of companies surviving the first screen for *Major* listings. The column headed *Region* contains the number of companies surviving the last screen eliminating regional listings and the like. The *Final* screen excludes companies which exhibit free-floating market value below 10 million USD. We further describe this final sample giving the number of a country's dead companies (#Dead) and the number of companies with at least one I/B/E/S estimate in the sample period (#I/B/E/S), along with respective percentage values (%-Dead and %-I/B/E/S). The last column gives the earliest month with sufficient Fama-French data. The table provides information for the U.S. in Panel A, while Panel B covers European countries.

Country	Abb.	Region	Screening of Country Lists				Sample: FMV> 10						Date
			Total	*Major*	*Region*	FMV> 10	#Dead	%Dead	#Return	%Return	#I/B/E/S	%I/B/E/S	FF
Panel A: USA													
USA	USA	America	36659	20030	7279	6272	2554	40.7%	6180	98.5%	4860	77.5%	Jul 92
Panel B: Europe													
Europe		Europe	29266	10522	9383	7019	1996	28.4%	6901	98.3%	5169	73.6%	
United Kingdom	UK	Europe	7677	3444	3232	2268	732	32.3%	2232	98.4%	1652	72.8%	Jul 87
Germany	GER	Europe	10740	1833	1525	1017	228	22.4%	991	97.4%	646	63.5%	Jan 88
Austria	A	Europe	360	177	161	119	31	26.1%	115	96.6%	80	67.2%	Jan 90
Switzerland	CH	Europe	1130	387	316	277	49	17.7%	274	98.9%	217	78.3%	Jan 90
France	FR	Europe	2643	1458	1368	945	258	27.3%	917	97.0%	631	66.8%	Jan 90
Italy	IL	Europe	794	390	365	345	95	27.5%	345	100 %	305	88.4%	Jan 90
Greece	GR	Europe	523	393	360	338	57	16.9%	338	100 %	234	69.2%	Jun 98
Spain	ES	Europe	311	204	180	170	51	30.0%	168	98.8%	160	94.1%	Feb 92
Portugal	POR	Europe	296	146	134	92	48	52.2%	91	98.9%	66	71.7%	Jun 97
Netherlands	NL	Europe	791	272	250	201	77	38.3%	199	99.0%	182	90.5%	Jan 90
Belgium	BEL	Europe	1000	288	263	206	40	19.4%	200	97.1%	129	62.6%	Jan 90
Sweden	SWE	Europe	1203	549	441	346	109	31.5%	344	99.4%	280	80.9%	Jan 90
Norway	NOR	Europe	585	328	284	254	98	38.6%	252	99.2%	219	86.2%	Jan 90
Denmark	DK	Europe	685	365	230	197	55	27.9%	197	100 %	167	84.8%	Jan 90
Finland	FN	Europe	341	190	180	159	42	26.4%	155	97.5%	138	86.8%	Mar 91
		All	65738	30454	16568	13206	4524	34.3%	12998	98.4%	9966	75.5%	
		Top 5	58922	27314	13845	10848	3881	35.8%	10664	98.3%	8094	74.6%	

To give an idea of the investment universe's size over time, we provide the absolute number of companies to be considered for the dispersion strategies across countries in Table 6.2. All in all, we have 58,510 firm-years of which one half is concentrated in the U.S. (32,787 firm-years), followed by the U.K. (4,514 firm-years) and France (4,182 firm-years). Note that the number of available companies usually increases over the years, with a peak in 1999 followed by a slight setback.

6.1.2 Return Data

We consider monthly stock returns in local currency inclusive of dividends by employing total return figures. To represent the respective markets, we choose broad market indices as compiled by Datastream and 3-month-T-bills serve as a proxy for the risk-free rate. As we have already shown in Chapter 2 the price momentum effect cannot be detected when naïvely using raw Datastream data. Thus, we again follow Ince and Porter (2006) in adjusting the return data to allow for reasonable statistical and economic inferences. As mentioned in Section 5.2.2 our comprehensive sample is hardly confounded by erroneous return data. Still, the remaining issues might severely affect statistical inferences and weeding them out renders us even more comfortable with the quality of data.

6.2 Testing for the Dispersion Effect

6.2.1 Risk and Return

We implement the dispersion strategy as in Diether, Malloy, and Scherbina (2002), defining dispersion as the standard deviation of earnings forecasts over the absolute value of its mean. Based on the previous month's dispersion, we assign stocks monthly into five quintiles for larger countries or terciles for smaller countries, depending on the number of available companies. Adopting a holding period of one month the dispersion strategy is to long stocks with low dispersion and to short stocks with high dispersion in analysts' earnings forecasts.

Table 6.2: Country Universes by Year

The table gives the average number of companies to be considered for the dispersion strategy. Panel A covers the U.S. and Panel B covers European countries.

Year	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	Σ #
Panel A: USA																					
USA	803	867	937	936	1006	1131	1288	1409	1612	1861	2070	2151	2339	2197	1926	1772	2000	2095	2190	2197	32787
Panel B: European Countries																					
Europe	605	714	823	886	966	1024	1075	1187	1368	1466	1628	1742	1924	1804	1466	1215	1355	1419	1614	1776	26057
UK	152	146	127	141	159	161	191	189	220	264	291	279	328	268	207	171	247	291	319	363	4514
Germany	103	99	108	115	135	156	165	177	180	179	204	207	264	268	199	151	160	163	195	230	3458
Austria	14	19	22	27	31	33	33	38	41	40	36	36	37	31	24	18	20	19	28	34	581
Switzerland	70	83	95	95	93	96	97	95	100	105	112	119	127	133	129	109	108	105	129	132	2132
France	86	100	136	131	146	151	159	179	204	233	254	272	300	307	272	242	242	237	257	274	4182
Italy	17	29	37	37	39	34	30	35	41	41	55	65	68	75	68	61	66	75	99	114	1086
Greece	0	0	0	0	0	10	29	58	86	70	72	94	86	63	55	39	50	40	44	56	852
Spain	17	40	73	76	71	65	65	67	69	68	79	90	96	91	83	74	77	74	79	84	1438
Portugal	0	0	0	0	6	23	26	30	34	33	38	42	42	27	12	8	5	10	14	16	366
Netherlands	56	72	84	91	94	94	95	99	109	113	118	130	137	124	101	87	88	85	85	86	1948
Belgium	24	25	25	29	31	31	35	41	46	48	58	70	72	73	72	55	60	57	62	65	979
Sweden	10	12	13	34	36	37	38	46	63	78	101	119	132	116	77	61	76	82	92	96	1319
Norway	9	11	13	15	19	19	20	22	38	47	54	53	59	62	45	28	36	45	66	76	737
Denmark	33	62	75	77	89	93	56	59	67	72	80	80	79	77	52	39	45	61	61	58	1315
Finland	7	9	8	12	9	11	24	40	52	56	52	63	75	66	52	52	53	52	60	63	816
Σ	1401	1574	1753	1816	1964	2145	2351	2584	2962	3308	3674	3870	4241	3978	3374	2967	3333	3491	3780	3944	58510

Table 6.3 gives average monthly buy-and-hold return and volatility figures of dispersion-based portfolios by country. First, we assess the profitability of the dispersion hedge strategy by considering the return differential—low dispersion minus high dispersion stocks—along with its t-statistic. For the U.S., we confirm prior evidence of Diether, Malloy, and Scherbina (2002) or Avramov, Chordia, Jostova, and Philipov (2008). We obtain a monthly hedge return of 49 basis points at a monthly volatility of 3.85%, which give rise to a t-statistic of 1.98. Note that the returns of the dispersion-based portfolios decrease monotonically with increasing dispersion, while their volatility is positively related to dispersion. The aggregate European hedge strategy provides a somewhat smaller return of 38 basis points per month, but at a considerably lower volatility of 2.87%. Further, using the t-statistic metric, we identify the Netherlands to have an anomalous returns on a 5% level. If we relax the significance level to 10%, Germany, Italy and Sweden appear to be anomalous as well. With the exception of Norway, all of the remaining countries exhibit positive return differentials. While the low dispersion portfolio is sometimes contributing significantly to the return spread, we note that the lion's share is typically due to the high dispersion portfolio.

Given this persuasive evidence of international dispersion effects, we seek to further characterize the involved dispersion portfolios by examining some descriptive statistics in Table 6.4. First of all, inspecting the average dispersion of the available dispersion-based portfolios suggests that the dispersion in analysts' earnings forecasts follows a heavily right-skewed distribution. Especially, the average dispersion of the high dispersion is rather large. For instance, while the fourth U.S. quintile portfolio has an average dispersion of 7.52%, the high dispersion portfolio figure amounts to 55.32%. Note that this pattern is even more pronounced for the European countries. Just consider the high dispersion portfolio of the European strategy, which is characterized by a mean dispersion in excess of 100% indicating considerable disagreement among the analysts. On the other hand, the low dispersion portfolio has mean dispersion of 2.39%, which is indicative of a strong consensus among the analysts. Moreover, across all countries the dispersion-based portfolios' volatility is increasing with dispersion, which calls for controlling of a systematic risk bias possibly inherent in these portfolios. Thus, we compute betas according to the classical regression

$$R_{it} - R_{Ft} = \alpha_i + \beta_i(R_{Mt} - R_{Ft}) + \varepsilon_{it}, \tag{6.1}$$

Table 6.3: Return and Volatility of Dispersion Portfolios

The table gives average monthly buy-and-hold returns and volatility of quintile or tercile portfolios that are built monthly dependent on the level of dispersion. All figures refer to the period from July 1987 to June 2007. We give the return differential of the respective hedge strategies along with the according t-statistic.

		Portfolio Dispersion Ranking						
Country		Low	2	Mid	4	High	*Low − High*	t-statistic
USA	Return	1.56	1.16	1.11	1.23	1.07	0.49	1.98
	Volatility	4.32	4.32	4.91	5.66	6.71	3.85	
Europe	Return	1.24	1.14	1.13	1.10	0.87	0.38	2.04
	Volatility	3.96	4.27	4.71	4.86	5.68	2.87	
UK	Return	1.15	1.13	1.00	1.05	0.99	0.16	0.72
	Volatility	4.09	4.51	4.42	4.88	5.71	3.44	
Germany	Return	0.94	0.87	0.75	0.92	0.45	0.49	1.95
	Volatility	5.11	5.46	5.56	5.77	7.28	3.88	
Austria	Return	1.56		1.25		1.26	0.30	0.93
	Volatility	5.63		5.70		6.38	4.58	
Switzerland	Return	0.93	1.08	0.95	0.80	0.87	0.05	0.24
	Volatility	4.69	5.14	5.82	5.85	6.32	3.56	
France	Return	1.35	1.32	1.25	1.00	1.05	0.30	1.20
	Volatility	5.15	5.46	6.03	6.27	7.05	3.92	
Italy	Return	0.94	0.94	0.91	0.93	0.39	0.52	1.92
	Volatility	6.22	6.85	6.43	6.39	7.52	4.16	
Greece	Return	2.15		1.75		1.99	0.16	1.17
	Volatility	9.50		9.37		10.72	3.55	
Spain	Return	1.47	1.48	0.99	1.28	1.12	0.38	1.29
	Volatility	5.06	6.10	6.46	6.84	7.68	4.62	
Portugal	Return	1.67		1.22		1.20	0.31	0.66
	Volatility	5.96		5.59		6.58	5.50	
Netherlands	Return	1.51	1.30	1.38	1.21	0.86	0.63	2.22
	Volatility	4.39	5.02	5.11	5.82	6.67	4.38	
Belgium	Return	1.12		1.19		0.85	0.26	0.62
	Volatility	4.56		5.19		5.48	2.91	
Sweden	Return	1.75	1.73	1.57	1.61	1.11	0.65	1.83
	Volatility	5.92	6.47	6.54	6.89	8.09	5.47	
Norway	Return	1.42		1.49		1.43	-0.01	-0.19
	Volatility	6.62		6.92		8.45	5.87	
Denmark	Return	1.35	1.33	1.24	1.27	1.02	0.33	1.21
	Volatility	4.68	4.88	4.73	4.70	5.61	4.21	
Finland	Return	1.57		1.56		1.45	0.12	0.72
	Volatility	6.57		7.29		8.04	5.18	

where R_{it} denotes the gross return of quintile i, R_{Ft} is the risk-free rate and R_{Mt} is the country's market return. Unsurprisingly, the beta of the dispersion-based portfolios is also increasing with dispersion. Moreover, in all countries the highest betas obtain for the high dispersion quintile. Also, while the remaining portfolios with lower dispersion have rather homogenous size characteristics, we observe a severe size bias on behalf of the high dispersion portfolio. In particular, measuring size in terms of the logarithm of market value, we find that the high dispersion portfolio is mostly populated by small caps, which may in turn explain its conspicuous market exposure. Finally, turning to the hedge strategy we almost always observe considerable negative exposure to the market portfolio, suggesting distinct hedge potential with respect to market risk.

Table 6.4: Descriptive Statistics of Dispersion Portfolios

The table gives mean values of dispersion as well as two risk proxies, beta and log-size, over the whole period. Quintile and tercile portfolios are built monthly dependent on the level of dispersion. As for risk proxies we consider the quintile portfolios' betas (arising from a standard CAPM) and size being measured as the average of log(marketvalue).

		Portfolio Dispersion Ranking					
Country		Low	2	Mid	4	High	*Low − High*
	Dispersion	0.66	2.14	3.83	7.52	55.32	
USA	Beta	0.77	0.79	0.94	1.09	1.30	-0.53
	Size	20.53	20.74	20.45	20.14	19.78	
	Dispersion	2.39	5.68	9.51	16.70	101.82	
Europe	Beta	0.87	0.95	1.05	1.10	1.28	-0.41
	Size	21.92	21.65	21.15	20.65	20.08	
	Dispersion	1.59	3.11	4.70	7.37	38.24	
UK	Beta	0.71	0.76	0.76	0.85	0.99	-0.29
	Size	24.57	25.00	25.08	25.19	24.87	
	Dispersion	3.34	7.24	11.73	21.02	122.71	
Germany	Beta	1.06	1.12	1.17	1.23	1.52	-0.45
	Size	20.25	20.56	20.51	20.26	19.71	
	Dispersion	3.71		9.89		59.95	
Austria	Beta	1.09		1.10		1.27	-0.18
	Size	19.68		19.88		19.31	
	Dispersion	3.61	7.76	12.55	21.05	113.53	
Switzerland	Beta	0.97	1.07	1.21	1.22	1.29	-0.32
	Size	20.60	20.76	20.59	20.41	20.00	
	Dispersion	3.02	6.26	9.80	16.30	114.66	
France	Beta	0.96	1.03	1.18	1.22	1.38	-0.38
	Size	20.13	20.61	20.40	20.18	19.63	
	Dispersion	4.16	8.88	13.00	19.39	61.32	
Italy	Beta	0.91	1.00	0.94	0.98	1.17	-0.27
	Size	20.63	20.81	20.71	20.40	20.17	
	Dispersion	6.05		14.36		42.74	
Greece	Beta	0.76		0.73		0.88	-0.11
	Size	19.59		19.57		19.14	
	Dispersion	3.54	7.18	11.05	17.08	70.31	
Spain	Beta	0.77	0.90	0.93	1.01	1.13	-0.40
	Size	20.69	20.79	20.46	20.21	19.50	
	Dispersion	6.90		15.89		60.98	
Portugal	Beta	0.74		0.77		0.88	-0.14
	Size	20.35		20.07		19.46	
	Dispersion	2.12	4.51	7.29	12.61	97.50	
Netherlands	Beta	0.79	0.94	0.95	1.13	1.25	-0.46
	Size	19.93	20.01	19.87	19.61	18.83	
	Dispersion	4.48		11.41		73.16	
Belgium	Beta	1.07		1.25		1.30	-0.23
	Size	20.44		20.33		19.70	
	Dispersion	3.78	7.84	12.62	21.59	116.86	
Sweden	Beta	0.61	0.71	0.72	0.73	1.01	-0.40
	Size	22.22	22.62	22.47	22.31	22.03	
	Dispersion	6.21		14.81		140.81	
Norway	Beta	0.81		0.88		1.07	-0.26
	Size	21.71		22.02		21.62	
	Dispersion	3.66	8.06	13.81	24.21	147.75	
Denmark	Beta	1.10	1.00	1.07	1.10	1.29	-0.18
	Size	21.22	21.49	21.31	21.26	20.83	
	Dispersion	6.45		17.48		76.61	
Finland	Beta	0.87		0.95		1.12	-0.25
	Size	19.62		19.81		19.59	

6.2.2 Time-Series Regressions

Some of the examined dispersion strategies are highly volatile and we thus wonder whether their high returns are solely compensating for risk. To check if the long-short portfolio returns can be attributed to common risk factors one usually adopts the standard approach of Fama and French (1993) and estimates a regression model of the form

$$R_{Lt} - R_{St} = \alpha + \beta(R_{Mt} - R_{Ft}) + \gamma R_{SMBt} + \delta R_{HMLt} + \varepsilon_t, \tag{6.2}$$

where $R_{Lt} - R_{St}$ is the return difference of the respective hedge strategy, i.e., the long leg minus the short leg. Regarding the country-specific common risk factor portfolios, the market return R_{Mt} is represented by some broad market index, the size factor R_{SMBt} is mimicked by a small cap index minus the risk-free rate, $R_{SCt} - R_{Ft}$, and the value factor R_{HMLt} is the difference between a value index and the corresponding growth index, $R_{Vt} - R_{Gt}$. Given the factor structure in (6.2), we can identify the hedge strategy's alpha net of common risk factors.

In addition to the Fama-French factors, one commonly considers momentum as a further factor to control for. We conjecture earnings momentum to be closely related to the dispersion effect. Indeed, in untabulated results, we find earnings momentum and the dispersion effect to be highly correlated in terms of returns and Fama-French alphas. While a high return correlation may simply be picking up systematic risk factor tilts shared by both anomalies, the high correlation in Fama-French alphas suggests that there is a common unsystematic component at work as well. Therefore, when testing for the dispersion effect, we extend the Fama-French setting of equation (6.2) to a four-factor model by adding an earnings momentum factor:

$$R_{Lt} - R_{St} = \alpha + \beta(R_{Mt} - R_{Ft}) + \gamma R_{SMBt} + \delta R_{HMLt} + \zeta R_{PMNt} + \varepsilon_t, \tag{6.3}$$

where R_{PMNt} refers to the returns of the earnings momentum strategy (positive minus negative earnings revisions). In computing the earnings momentum factor, we follow the standard methodology of Chan, Jegadeesh, and Lakonishok (1996).

Table 6.5 displays the results of the four-factor regression for dispersion-based portfolios according to equation (6.3) that uses 240 monthly returns spanning the period from July 1987 to June 2007. First, we examine the results for the U.S.. We observe that the risk factors explain most of the variation in the excess returns of both legs of the dispersion strategy.

Table 6.5: Time-Series-Regressions of Dispersion Portfolios

The Table gives the results of a regression according to Equation (6.3) using 240 monthly returns ranging from July 1987 to June 2007 along with the according t-statistics.

		Fama-French Model										
		α	β	γ	δ	ζ	$t(\alpha)$	$t(\beta)$	$t(\gamma)$	$t(\delta)$	$t(\zeta)$	Adj. R^2
USA	Low	-0.01	0.70	0.17	0.03	0.44	-0.05	14.88	3.33	0.62	7.45	79.4
	High	-0.57	0.91	0.48	-0.17	-0.27	-4.47	20.64	10.10	-4.14	-4.78	92.8
	Low-High	0.56	-0.22	-0.31	0.19	0.71	3.24	-3.61	-4.82	3.52	9.26	62.9
Europe	Low	0.45	0.37	0.45	0.00	0.23	4.88	7.81	12.64	-0.04	4.83	91.2
	High	0.26	0.86	0.34	-0.21	-0.43	1.97	12.73	6.54	-4.12	-6.30	92.2
	Low-High	0.19	-0.49	0.12	0.21	0.65	1.15	-5.86	1.81	3.29	7.76	55.7
UK	Low	0.39	-0.12	0.80	-0.13	0.18	3.58	-1.58	11.06	-3.23	3.51	82.2
	High	0.53	0.46	0.47	-0.01	-0.40	2.84	3.48	3.77	-0.16	-4.63	75.4
	Low-High	-0.14	-0.59	0.34	-0.12	0.57	-0.68	-4.07	2.51	-1.60	6.18	29.9
Germany	Low	-0.13	0.79	0.29	-0.03	0.19	-0.83	11.96	5.07	-0.71	3.01	79.6
	High	-0.56	1.43	0.11	-0.15	-0.31	-2.56	15.55	1.38	-2.75	-3.50	82.2
	Low-High	0.43	-0.64	0.18	0.12	0.51	2.06	-7.29	2.39	2.35	5.97	44.2
Austria	Low	0.49	0.82	0.35	-0.02	0.04	2.37	10.58	5.47	-0.65	0.88	71.2
	High	0.03	0.88	0.37	0.03	-0.05	0.15	10.59	5.42	0.63	-0.95	72.4
	Low-High	0.46	-0.06	-0.02	-0.05	0.09	1.53	-0.58	-0.26	-0.92	1.32	1.0
Switzerland	Low	-0.09	0.86	0.11	0.01	0.14	-0.79	14.84	2.21	0.39	3.66	86.0
	High	-0.06	1.06	0.20	0.07	-0.41	-0.43	14.99	3.27	2.09	-9.10	90.4
	Low-High	-0.03	-0.20	-0.09	-0.06	0.55	-0.16	-2.08	-1.08	-1.31	9.01	46.8
France	Low	-0.03	0.87	0.13	-0.03	0.11	-0.17	15.29	2.56	-0.82	1.79	79.4
	High	-0.25	0.95	0.38	0.00	-0.35	-1.51	16.56	7.45	-0.01	-5.89	89.1
	Low-High	0.22	-0.08	-0.25	-0.03	0.47	0.99	-1.07	-3.84	-0.59	5.95	40.2
Italy	Low	-0.04	0.84	0.08	-0.14	0.14	-0.21	9.79	0.92	-3.28	2.23	76.4
	High	-0.51	1.10	0.04	-0.09	-0.34	-2.90	14.38	0.45	-2.23	-6.05	87.2
	Low-High	0.47	-0.26	0.04	-0.06	0.48	2.02	-2.58	0.41	-1.07	6.44	27.5
Greece	Low	0.12	0.51	0.36	-0.41	0.03	0.45	11.69	7.17	-3.81	0.51	88.0
	High	-0.15	0.60	0.38	-0.35	-0.09	-0.51	12.58	6.86	-2.97	-1.39	89.0
	Low-High	0.27	-0.09	-0.02	-0.06	0.13	1.00	-2.05	-0.32	-0.56	2.01	14.2
Spain	Low	0.04	0.64	0.21	-0.06	0.14	0.23	10.71	3.29	-1.43	3.95	79.5
	High	-0.40	0.93	0.23	-0.04	-0.19	-2.11	13.08	3.04	-0.93	-4.53	85.8
	Low-High	0.43	-0.29	-0.02	-0.01	0.34	1.76	-3.12	-0.21	-0.21	5.98	33.8
Portugal	Low	-0.33	0.37	0.52	-0.01	0.33	-1.06	4.87	9.13	-0.10	6.00	59.0
	High	-0.33	0.44	0.54	-0.16	-0.12	-1.02	5.50	9.12	-2.02	-2.14	62.6
	Low-High	0.00	-0.07	-0.03	0.15	0.45	0.01	-0.70	-0.35	1.56	6.36	19.3
Netherlands	Low	0.48	0.78	0.04	-0.03	0.17	3.37	12.67	0.62	-1.11	4.23	75.1
	High	-0.06	1.07	0.08	0.04	-0.37	-0.33	14.27	1.15	1.06	-7.48	84.8
	Low-High	0.53	-0.29	-0.05	-0.08	0.54	2.33	-3.01	-0.51	-1.51	8.43	45.7
Belgium	Low	0.07	0.67	0.35	0.04	0.08	0.56	10.57	7.35	1.08	1.99	80.9
	High	-0.14	0.97	0.27	0.02	-0.20	-0.86	12.71	4.73	0.50	-4.23	81.2
	Low-High	0.21	-0.30	0.08	0.02	0.28	1.10	-3.25	1.17	0.33	4.91	16.1
Sweden	Low	0.35	0.44	0.29	0.06	0.20	1.44	7.36	4.08	1.70	3.28	58.8
	High	-0.34	0.79	0.27	-0.06	-0.17	-1.48	14.35	4.15	-1.92	-3.04	81.9
	Low-High	0.69	-0.35	0.02	0.12	0.37	2.34	-4.98	0.18	2.90	5.08	36.9
Norway	Low	0.08	0.53	0.32	-0.01	0.17	0.34	7.41	4.80	-0.15	3.45	66.4
	High	-0.04	0.55	0.50	0.09	-0.06	-0.15	6.43	6.38	1.55	-1.00	71.0
	Low-High	0.13	-0.01	-0.18	-0.10	0.23	0.36	-0.13	-1.96	-1.42	3.32	13.1
Denmark	Low	0.03	0.73	0.33	-0.02	0.02	0.14	8.85	5.37	-0.44	0.52	68.6
	High	-0.50	0.93	0.39	-0.07	-0.07	-2.34	9.46	5.42	-1.78	-1.38	71.3
	Low-High	0.53	-0.20	-0.06	0.06	0.09	1.87	-1.52	-0.68	1.08	1.38	5.4
Finland	Low	0.28	0.57	0.32	-0.03	-0.01	1.10	6.55	3.93	-1.13	-0.15	72.2
	High	0.09	0.61	0.50	-0.02	-0.20	0.36	7.11	6.22	-0.78	-3.91	81.9
	Low-High	0.19	-0.04	-0.18	-0.01	0.19	0.53	-0.33	-1.58	-0.26	2.65	11.4

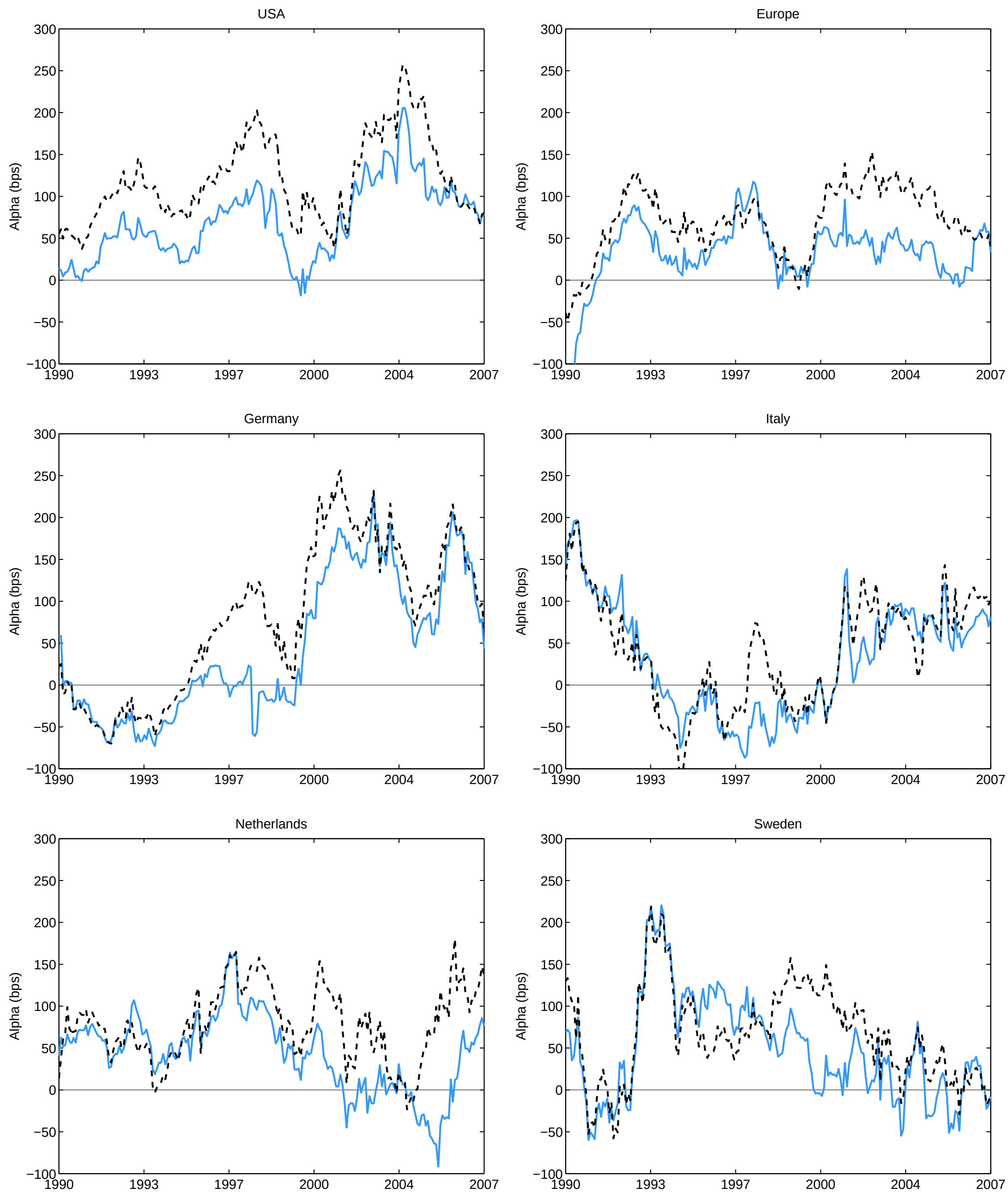
In particular, the low dispersion portfolio heavily loads to the market and earnings momentum factor and exhibits a minor size bias, rendering the remaining alpha of -1 basis points insignificant. On the other hand, the high dispersion portfolio generally behaves like small-sized growth stocks with a significant negative earnings momentum loading. Still, an unexplained alpha of -57 basis points remains; thus, the long-short strategy earns a highly significant monthly alpha of 56 basis points. Interestingly, while this alpha is large, the statistical fit of the regression is fairly good considering the fact that one is analyzing a long-short strategy. More than one half of the variation in the dispersion strategy's excess returns is captured by the four-factor model. In particular, we confirm the considerate negative market exposure together with a negative loading on size. Finally, we identify a close relation between earnings momentum and the dispersion effect. However, the dispersion effect is not subsumed by earnings momentum suggesting that both represent distinct phenomena.

By and large, these observations extend to other countries as well. Of the 15 European countries, we document four alphas that are significant on the 5%-level and relaxing the latter to 10%, we obtain six significant alphas—ranging from 43 basis points for the German and Spanish strategy to 69 basis points for the Swedish strategy. Also, it appears to be a stylized fact that the alpha of the dispersion effect is governed by the underperformance of the high dispersion portfolio. While the adjusted R^2 for European strategies usually do not reach the level of the U.S. strategy we still observe remarkably high values. Half of the regressions for the long-short strategies are characterized by adjusted R^2s in excess of 30%. These figures are quite sizeable given that typical values for long-short strategies are single-digited. Note that the returns for the aggregate European strategy are fully captured by the common factor controls.

To further examine the evolution of both hedge strategies over time, we compute the related country alphas via trailing four-factor regressions according to equation (6.3). We use a 36-month window and plot the resulting alphas in Figure 6.1 for the six strategies exhibiting significant hedge returns. To also visualize the importance of adjusting for the earnings momentum factor, we additionally plot the alphas arising from a Fama-French regression according to equation (6.2).

Figure 6.1: Trailing Alpha of the Dispersion Effect

We plot trailing dispersion strategy alphas arising from equations (6.2) and (6.3) using 36-months windows, thus results cover July 1990 to June 2007. The dashed line gives the Fama-French alpha and the solid line is the respective four-factor alpha.



First of all, we note that the inclusion of the earnings momentum factor is relevant, since the Fama-French alpha is significantly reduced in many countries. Also, while this reduction typically is present throughout the whole sample period, it appears to be weakest at the turn of the century. Second, the U.S. strategy exhibits the most sizeable alpha, which is significantly positive for the the whole sample period. Third, across the remaining countries the evolution of alpha appears downward shifted when compared to the U.S..

6.3 Data Snooping Biases and the Dispersion Effect

Recapitulating the results of the traditional analysis, we are left with six positive and significant dispersion effect return differentials as well as seven positive and significant dispersion effect alphas. Since this result could have occurred by chance alone, we will subject the dispersion hedge strategies to the econometric methods of Chapter 3 that additionally account for multiple testing issues.

To control the FWE, we consider the k-StepM method for $k = 1$, which is the appropriate choice given the number of strategies under study. To control the FDP, we pursue the FDP-StepM$_\gamma$ using $\gamma = 0.1$. We keep the significance level constant at 5% across all multiple testing procedures and we present results for the return of the hedge strategies as well as their alphas arising from the four-factor time series regressions. To account for potential serial correlation in the return series, we use a kernel variance estimator based on the Parzen kernel to studentize the test statistics, see Andrews (1991). The bootstrap method is the stationary bootstrap with an average block size of 12 months.

The left panel of Table 6.6 reports the multiple testing results for the countries' return statistics. We provide the lower confidence band c_l for the returns using studentized test statistics according to the StepM and FDP-StepM$_\gamma$ method, respectively. Since we are in a one-sided test setting, we give the lower limits of the confidence interval as computed in the last step of the respective method. The value in the column labeled rej equals 1 if $0 \notin [c_l, \infty)$, which indicates the rejection of capital market efficiency and suggests the presence of a dispersion effect in the respective country.

Table 6.6: Accounting for Multiple Testing in the Dispersion Effect

The table gives the lower confidence band c_l for the returns as obtained by the StepM method and the FDP-StepM$_{0.1}$using studentized test statistics as illustrated in Section 3.1. The *rej*-columns contain the resulting decision where 1 indicates rejection of $\theta_s = 0$ (capital market efficiency). The left panel provides results for returns as test statistics and the right panel provides results for 4-factor alphas as test statistics.

	Return					4-Factor Alpha				
Country	θ_s	*StepM*		*FDP-StepM*$_{0.1}$		θ_s	*StepM*		*FDP-StepM*$_{0.1}$	
		c_l	*rej*	c_l	*rej*		c_l	*rej*	c_l	*rej*
USA	0.0049	-0.0032	0	-0.0032	0	0.0056	-0.0015	0	-0.0015	0
Europe	0.0038	-0.0037	0	-0.0037	0	0.0019	-0.0028	0	-0.0028	0
UK	0.0016	-0.0074	0	-0.0074	0	-0.0014	-0.0092	0	-0.0092	0
Germany	0.0049	-0.0043	0	-0.0043	0	0.0043	-0.0021	0	-0.0021	0
Austria	0.0030	-0.0060	0	-0.0060	0	0.0046	-0.0050	0	-0.0050	0
Switzerland	0.0005	-0.0072	0	-0.0072	0	-0.0003	-0.0056	0	-0.0056	0
France	0.0030	-0.0050	0	-0.0050	0	0.0022	-0.0057	0	-0.0057	0
Italy	0.0052	-0.0031	0	-0.0031	0	0.0047	-0.0030	0	-0.0030	0
Greece	0.0016	-0.0061	0	-0.0061	0	0.0027	-0.0048	0	-0.0048	0
Spain	0.0038	-0.0064	0	-0.0064	0	0.0043	-0.0040	0	-0.0040	0
Portugal	0.0031	-0.0091	0	-0.0091	0	0.0000	-0.0115	0	-0.0115	0
Netherlands	0.0063	-0.0033	0	-0.0033	0	0.0053	-0.0005	0	-0.0005	0
Belgium	0.0026	-0.0028	0	-0.0028	0	0.0021	-0.0024	0	-0.0024	0
Sweden	0.0065	-0.0065	0	-0.0065	0	0.0069	-0.0020	0	-0.0020	0
Norway	-0.0001	-0.0120	0	-0.0120	0	0.0013	-0.0076	0	-0.0076	0
Denmark	0.0033	-0.0061	0	-0.0061	0	0.0053	-0.0027	0	-0.0027	0
Finland	0.0012	-0.0097	0	-0.0097	0	0.0019	-0.0085	0	-0.0085	0
Σ			0		0			0		0

Concerning the results for the returns, we do not observe any rejection of capital market efficiency by the StepM method. In this case the FDP-StepM$_\gamma$ coincides with the StepM, since the number of rejections does not exceed nine. The right panel of Table 6.6 displays the multiple testing results using the four-factor alphas as test statistics. With this metric the dispersion effect is again found to be vulnerable to data snooping biases. The StepM method yields no rejection of capital market efficiency, which implies equivalent results of the FDP-StepM$_\gamma$. Therefore, regardless of controlling the FWE or the FDP, none of the naïvely derived dispersion effects is really refuting capital market efficiency. This surprising result raises the need for sound economic inference.

6.4 Explaining the Dispersion Effect

Taking the results of the previous section at face value, one may be tempted to reject the notion of international dispersion effects right away. However, we hesitate to do so given the intriguing fact of almost always positive return differentials together with positive alphas. In reconciling these results with intuition, we further delve into the economic nature of the dispersion effect. First, we consider the evolution of the related strategies over time. Second, we will analyze the interaction of the dispersion effect with measures of information uncertainty. Third, we examine the profitability of dispersion strategies among varying levels of liquidity.

6.4.1 The Dispersion Effect over Time

In the following, we seek to sharpen our intuition about the time series nature of the dispersion effect. Therefore, Figure 6.2 depicts the cumulative return for the six strategies exhibiting significant hedge returns, i.e., the U.S., Europe, Germany, Italy, the Netherlands, and Sweden. Across countries a striking common pattern emerges: Following a steady build-up of wealth until the end of 1998 we observe a severe drawdown. For example, the U.S. strategy erodes half of its accumulated wealth within the subsequent year. The decline in performance is reversed for almost all countries in March 2000. Even more so, the dispersion strategy is soaring to a new height within the following three years. The most recent history is characterized by rather flat return paths across all countries.

Note that the general evolution of the European dispersion effects only resembles the one of the U.S. for the second half of the sample period. While the U.S. dispersion effect amasses significant wealth in the first half of the sample period, we state that the positive European return differentials mainly derive from a narrow time frame, namely March 2000 to March 2003. Comparing the dispersion strategy performance to the evolution of a broad market index, it appears that the dispersion strategy would have been a quite effective hedge against the burst of the tech bubble at the beginning of the century. To further disentangle the performance drivers of the dispersion effect, we investigate the performance of the low dispersion and the high dispersion portfolio in Figure 6.3.

Focussing on the time frame March 2000 to March 2003, we find the U.S. low dispersion portfolio significantly accumulating wealth, while the high dispersion portfolio is eroding wealth. On the other hand, the European low dispersion portfolios move sideways in the respective period. Hence, the resulting dispersion effects are solely driven by a severe underperformance of the short legs. This observation is quantified by the subperiod analysis conducted in Table 6.7 capturing the years 1998 to 2003.

Figure 6.2: Cumulative Returns: Dispersion versus Market Portfolio

The figures give cumulative total returns the dispersion hedge portfolios (solid line) and to a broad market index (dashed line). Results are for the period from July 1987 to June 2007.

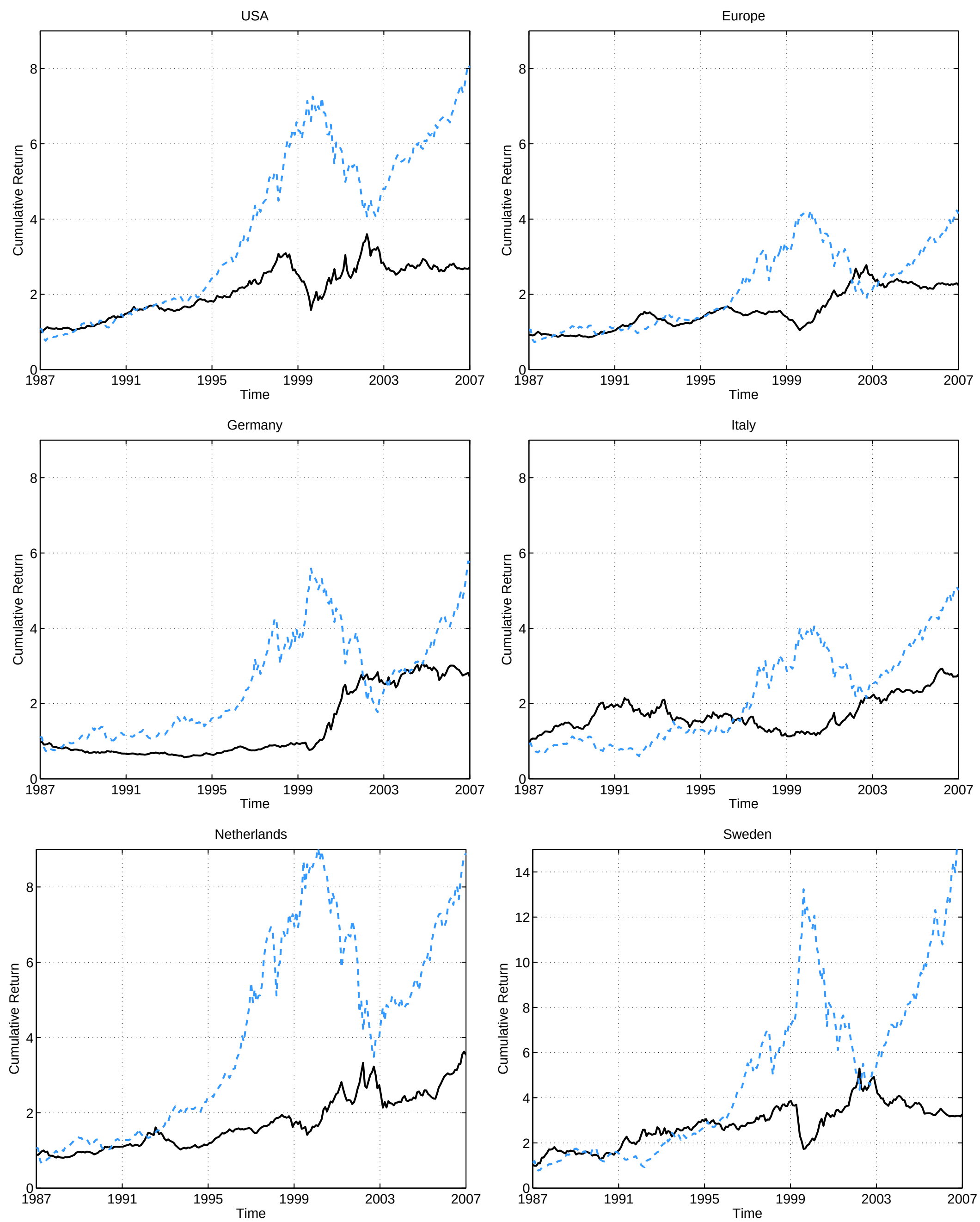
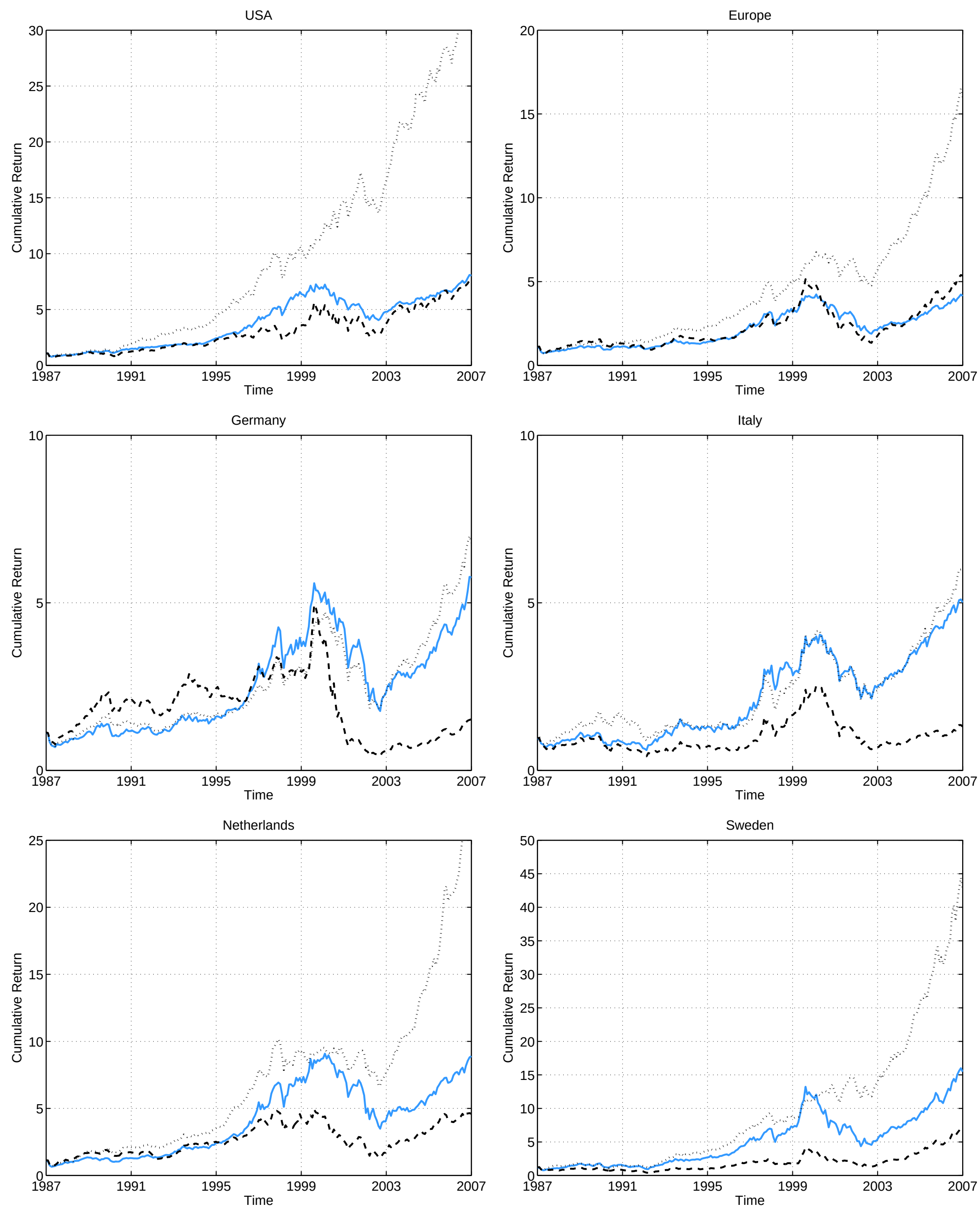


Figure 6.3: Cumulative Returns: Dispersion Legs versus Market Portfolio
The figures give cumulative total returns to the long and short leg of the dispersion hedge strategy. Results are for the period from July 1987 to June 2007. The solid line is for the market portfolio, the dotted line represents the low dispersion portfolio, and the dashed line represents the high dispersion portfolio.



The choice of breakpoints in Table 6.7 is motivated as follows: At the starting point April 1998 all of the dispersion strategies exhibit a total return level close or equal to their peak prior the subsequent decline in performance. This pattern of declining performance ends for almost all countries in April 2000 defining the second breakpoint. The following three years are marked by significant outperformance of the dispersion strategy reaching a global peak in April 2003, the end of the subperiod. Interestingly, the last breakpoint coincides with the dawn of the Iraq War in 2003.

Considering the subperiod 1998-2003 in Table 6.7, we find results that are quite similar to the ones documented for the whole sample period in Table 6.3. These results have been expected from our visual inspection of the cumulative return patterns. Of course, the resulting return differentials are more sizeable than those of the whole sample period, given that the European countries are characterized by rather flat return patterns outside the 5 year sub-period. Confirming our earlier assessment, the declining performance of the dispersion hedge strategy from 1998-2000 is almost always due to the extraordinary performance of the short leg. With the technology bubble bursting in March 2000, these high dispersion stocks then suffered extremely negative returns that have more than outweighed the dispersion strategies' previous losses. Of course, being short these companies would have been a favorable thing to do. However, we conjecture that the respective real-world implementation would have been rather unfeasible—just think of the up-tick rule. Of course, one may argue that most of the involved shorts would have already been in place at the beginning of 1999. However, with stock prices subsequently reaching unwarranted levels, one would have had trouble filling the according margin calls. Thus, many investors would have not been able to follow the dispersion strategy when it had really been profitable. These findings corroborate the doubts raised by the data snooping controls. Prior to 1999, only the U.S. dispersion effect has consistently provided abnormal returns. On the other hand the most sizeable part of the effects derive from a narrow time frame of 3 years. Hence, for really capturing the respective excess returns, it would have required a rather patient investor, equipped with 13 years waiting time, who is not wiped out of the strategy following the violent swing in 1999.

6.4.2 The Dispersion Effect and Information Uncertainty

In this section, we will analyze the interaction of the dispersion effect and information uncertainty. Presumably, the respective price drift should be higher in more opaque information environments for which information diffusion is slowest. In fact,

Table 6.7: The Dispersion Effect: Sub-Period Analysis

The table gives average monthly buy-and-hold returns and volatility of quintile or tercile portfolios that are built monthly dependent on the level of dispersion. The figures refer to the period from April 1998 to April 2003, the sub-period is further split in two at April 1st, 2000. We give the return differential of the respective hedge strategies, *Lo-Hi*, along with the according *t*-statistic.

Country	*1998-2003*				*1998-2000*				*2000-2003*			
	Low	High	Lo-Hi	*t*	Low	High	Lo-Hi	*t*	Low	High	Lo-Hi	*t*
USA	0.71	0.12	0.58		0.51	2.52	-2.01		0.83	-1.37	2.19	
	4.93	9.80	6.55	0.69	5.60	8.79	5.18	-1.86	4.54	10.21	6.85	1.95
EUR	0.13	-0.93	1.06		1.25	2.89	-1.64		-0.57	-3.31	2.75	
	4.40	7.44	4.03	2.04	4.64	6.62	2.69	-2.93	4.16	6.99	3.83	4.36
UK	0.17	-0.27	0.44		0.63	3.55	-2.92		-0.12	-2.65	2.53	
	4.33	7.97	5.69	0.60	4.59	8.45	6.36	-2.20	4.19	6.74	4.09	3.76
GER	-0.54	-2.65	2.12		1.90	2.41	-0.50		-2.05	-5.80	3.74	
	6.96	10.60	5.84	2.81	6.62	8.02	4.03	-0.60	6.81	10.88	6.23	3.66
A	0.03	-0.60	0.63		-0.55	0.55	-1.09		0.39	-1.31	1.70	
	4.94	4.72	4.71	-0.16	5.67	4.59	4.28	-1.11	4.47	4.72	4.70	0.58
CH	-0.26	-0.99	0.73		0.87	2.49	-1.62		-0.96	-3.15	2.19	
	5.09	8.12	4.65	1.22	5.63	8.30	3.28	-2.37	4.66	7.31	4.81	2.77
FR	0.26	-0.48	0.74		1.70	2.81	-1.11		-0.63	-2.52	1.89	
	5.44	9.10	5.35	1.07	6.01	7.77	3.91	-1.36	4.92	9.36	5.84	1.97
IL	-0.25	-1.14	0.88		1.78	2.15	-0.37		-1.51	-3.18	1.66	
	7.02	8.87	4.75	1.44	8.24	8.43	4.16	-0.43	5.93	8.62	4.98	2.03
GR	1.77	1.93	-0.16		10.07	11.52	-1.44		-3.39	-4.02	0.64	
	13.67	15.56	4.18	-0.62	16.45	18.71	5.26	-1.36	8.35	9.35	3.17	0.78
ES	0.35	-0.17	0.52		-0.34	0.88	-1.22		0.78	-0.82	1.60	
	5.02	6.97	3.90	1.03	6.82	8.55	3.31	-1.77	3.51	5.82	3.89	2.50
POR	0.75	-0.70	1.45		2.68	0.32	2.36		-0.45	-1.34	0.89	
	7.91	6.98	6.85	1.62	11.24	6.73	8.12	1.13	4.64	7.14	5.98	1.16
NL	-0.48	-1.77	1.30		-0.12	0.41	-0.53		-0.70	-3.13	2.43	
	4.62	8.40	5.76	1.74	5.14	7.31	5.11	-0.50	4.33	8.83	5.92	2.50
BEL	-0.51	-1.09	0.58		0.31	0.05	0.27		-1.02	-1.80	0.78	
	4.51	5.38	3.19	0.63	5.10	5.29	3.60	0.74	4.10	5.38	2.94	0.12
SWE	0.63	-0.33	0.95		1.28	3.53	-2.25		0.22	-2.72	2.95	
	4.97	10.53	7.41	1.00	4.98	11.73	8.04	-1.34	4.98	9.08	6.30	2.84
NOR	-0.13	-0.98	0.85		0.53	0.40	0.13		-0.54	-1.84	1.30	
	6.57	7.39	4.81	0.85	8.17	9.06	4.61	-0.64	5.42	6.10	4.93	1.33
DK	-0.18	-0.40	0.22		0.34	-0.24	0.58		-0.50	-0.50	-0.01	
	4.88	6.40	4.97	0.34	3.81	4.96	3.62	0.76	5.47	7.21	5.70	-0.01
FN	0.21	-0.42	0.63		1.78	1.00	0.78		-0.77	-1.30	0.53	
	5.97	7.15	3.13	0.90	8.10	8.78	2.75	0.77	3.98	5.87	3.39	0.56

dispersion of analysts' earnings forecasts itself is a common proxy for information uncertainty. Besides this metric, Zhang (2006) recently provides evidence that the U.S. price momentum strategy is more effective when limited to highly uncertainty stocks as measured by size, firm age, analyst coverage, stock volatility, or cash flow volatility. If the dispersion effect is confined to highly uncertain information environments investors would certainly be less prone to follow such a strategy. Hence, we will examine dispersion effect profits for different degrees of information uncertainty. We consider four measures to monthly proxy for information uncertainty: Analyst coverage, size, total stock volatility, and idiosyncratic volatility. Total stock volatility is estimated using the last three year's monthly stock returns, and idiosyncratic volatility arises from a standard Fama-French regression that also uses the last three year's monthly stock returns.

Table 6.8 gives the according results using a similar sorting procedure as in the previous section. In particular, we first sort stocks into five quintiles based on dispersion. For each quintile the stocks are further sorted into three terciles based on one of the three information uncertainty proxies. Obviously, this double-sorting procedure requires a sufficient amount of companies in a given country to deliver meaningful results. Hence, we exclude the six smallest countries, which are Austria, Belgium, Finland, Greece, Norway, and Portugal.

Our findings are as follows. First, the dispersion effect is hardly present when limited to high and low dispersion stocks with high analyst coverage. Nevertheless, the effect is not confined to low coverage stocks. Second, using size as the metric of information uncertainty provides the most poignant results: The dispersion effect cannot be detected when focussing on large cap companies.

Table 6.8: The Dispersion Effect and Information Uncertainty

The table gives return differentials of the dispersion hedge strategy by terciles of different information uncertainty metrics. We first sort stocks into five quintiles based on the prior month's dispersion in analysts' earnings forecasts. For each quintile the stocks are further sorted into three terciles based on analyst coverage, size, total stock volatility, and idiosyncratic volatility (arising from a rolling 36-months Fama-French regression). Below the return differentials we give t-statistics. The two last rows collect the number of countries that exhibit the highest return differential among the respective terciles and the terciles mean ranking in terms of returns.

Country	*Analyst Coverage*			*Size*			*Volatility*			*Idiosyncratic*		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
USA	0.74	0.58	0.26	0.76	0.60	0.32	0.32	0.78	1.49	0.92	1.05	1.42
	3.41	2.43	0.79	3.17	2.33	1.09	1.62	4.05	6.36	3.04	4.52	6.17
EUR	0.44	0.49	0.32	0.76	0.41	0.24	0.41	0.33	0.69	0.83	0.66	0.68
	2.59	2.51	1.31	3.69	2.47	1.01	3.21	2.28	3.64	4.08	3.38	3.49
UK	0.48	0.06	-0.13	1.19	0.03	-0.09	0.18	0.36	0.43	0.07	0.38	0.50
	1.48	0.19	-0.58	2.92	0.09	-0.35	0.92	1.60	1.26	0.25	1.48	1.66
GER	-0.10	0.83	0.31	1.09	0.54	0.09	0.11	0.81	0.83	0.60	0.72	0.95
	-0.23	2.72	0.91	2.35	1.56	0.27	0.33	2.85	2.54	1.81	2.21	3.03
CH	-0.66	0.29	0.18	0.56	-0.33	0.06	-0.09	0.12	0.49	0.46	0.24	0.32
	-1.87	0.95	0.55	1.17	-1.15	0.19	-0.35	0.43	1.44	1.71	0.80	0.94
FR	0.79	0.55	-0.32	0.43	0.25	0.18	0.30	-0.03	1.30	0.94	0.92	1.02
	2.22	1.71	-0.87	0.89	0.73	0.58	1.07	-0.09	3.99	3.48	2.89	2.99
IL	-0.81	1.23	0.60	-0.93	0.43	0.58	0.28	0.10	1.21	0.98	0.61	0.77
	-1.66	2.33	1.55	-1.81	0.98	1.48	0.76	0.26	2.28	2.20	1.33	1.68
ES	0.03	0.54	0.41	-0.09	0.41	0.68	0.57	1.22	0.29	0.73	0.66	0.22
	0.07	1.26	0.81	-0.18	1.06	1.08	1.00	2.73	0.55	1.66	1.98	0.55
NL	1.30	0.44	0.16	1.35	0.59	-0.33	0.35	0.48	0.96	0.93	0.92	1.18
	3.73	1.06	0.35	3.22	1.52	-0.69	0.96	1.28	1.89	2.62	2.69	2.87
SWE	0.04	1.05	0.26	-0.25	0.85	0.19	0.27	0.80	1.26	0.56	1.47	1.10
	0.07	2.32	0.56	-0.34	1.56	0.45	0.56	1.77	2.02	1.03	2.86	2.08
DK	0.61	0.45	-0.08	-0.01	0.46	-0.17	1.95	0.42	-0.28	1.31	0.89	-0.27
	1.25	1.16	-0.18	-0.02	1.08	-0.47	2.98	1.10	-0.59	2.00	2.18	-0.60
# max	5	6	0	7	2	2	1	1	9	5	1	5
ranking	2.00	1.45	2.55	1.64	1.91	2.45	2.45	2.18	1.36	1.91	2.36	1.73

Also, the dispersion effect is most pronounced when restricted to high volatility stocks. This relates to our finding that the dispersion effect is crucially driven by the short leg, which is mostly populated by high volatility stocks. Third, inspecting the results for idiosyncratic volatility reveals a more diverse pattern, in particular, the dispersion effect works either good when limited to low or high idiosyncratic volatility stocks. The latter result is especially telling as to why the dispersion effect has been difficult to arbitrage. In fact, a stock's idiosyncratic volatility is a common proxy for arbitrage costs and we find the dispersion effects to be most pronounced in stocks exhibiting high idiosyncratic volatility. Therefore, we contend that high arbitrage costs have prevented rational investors from exploiting the dispersion effect.

6.4.3 The Dispersion Effect and Liquidity

In further elaborating on the above argument we next examine the role of liquidity when implementing dispersion strategies. In fact, Sadka and Scherbina (2007) evidence that high dispersion companies happen to entail high trading cost. Also, the authors observe the highest mispricing for the less liquid stocks suggesting that trading costs erode all of the potential profits rendering the arbitrage opportunity an illusion. Hence, we expect liquidity to also play a crucial role in inhibiting profitable execution of European dispersion strategies.

To operationalize this conjecture we will analyze the profitability of the dispersion strategies when restricting to high and low dispersion stocks characterized by different degrees of liquidity. In doing so, we will resort to the very same liquidity metrics introduced in Section 5.6.3: A stock's dollar volume or its turnover allow to capture the trading quantity dimension. As for the price impact dimension we use the *ILLIQ* measure of Amihud (2002) which is the absolute daily return over the associated dollar volume. To obtain an aggregate monthly value of *ILLIQ* we simply compute its mean over the corresponding daily values. The fourth measure is the one introduced by Liu (2006) which captures multiple dimensions of liquidity, such as trading speed and trading quantity. We recapitulate its definition:

$$\text{Liu Measure} = \text{Number of No-Trading Days over the prior 12 months} + \frac{1/\text{Turnover}}{1,000,000}$$

where turnover is the average daily turnover over the prior 12 months.[1]

[1] Note that while the first three measures only take into account the stocks' liquidity over the precedent month the Liu measure hinges on data of the preceding year.

This measure addresses the trading speed dimension of liquidity since it very well captures lock-in-risk, i.e., the danger of being locked in a certain position that cannot be sold.

Table 6.9 displays the profitability of dispersion strategies restricted to high and low dispersion stocks characterized by different degrees of liquidity. In particular, we first sort stocks into five quintiles based on dispersion in analysts' earnings forecasts. For each quintile the stocks are further sorted into three terciles based on one of the four liquidity measures. Again, we exclude the six smallest countries from the analysis, i.e., Austria, Belgium, Finland, Greece, Norway, and Portugal.

Table 6.9: The Dispersion Effect and Liquidity

The table gives return differentials of the dispersion hedge strategy by terciles of different liquidity metrics. We first sort stocks into five quintiles based on the prior month's dispersion in analysts' earnings forecasts. For each quintile the stocks are further sorted into three terciles based on dollar volume, share turnover, the ILLIQ measure of Amihud (2002), and Liu's measure. Below the return differentials we give t-statistics. The last two rows collect the number of countries that exhibit the highest return differential among the respective terciles and the terciles mean ranking in terms of returns. We use the country abbreviations introduced in Table 5.1.

Country	*Dollar Volume*			*Share Turnover*			*ILLIQ*			*Liu Measure*		
	High	Mid	Low	High	Mid	Low	Low	Mid	High	Low	Mid	High
USA	0.34	0.41	0.48	0.59	0.42	0.46	0.28	0.42	0.61	0.74	0.29	0.35
	1.08	1.65	2.25	2.09	1.66	2.26	0.97	1.57	2.70	2.64	1.19	1.74
EUR	0.07	0.39	0.59	0.13	0.46	0.40	0.12	0.33	0.49	0.43	0.19	0.48
	0.31	2.09	3.55	0.55	2.31	2.51	0.56	1.73	2.79	1.77	1.06	3.36
UK	0.04	0.35	0.57	0.27	0.17	0.55	0.05	0.12	0.66	0.27	0.19	0.41
	0.17	1.39	2.04	1.00	0.74	2.15	0.21	0.45	2.51	1.07	0.73	1.56
GER	0.33	0.64	0.56	0.69	0.27	0.65	0.31	0.36	0.90	0.43	0.60	0.67
	0.98	2.28	1.54	2.08	1.02	1.80	1.06	1.29	2.33	1.43	2.17	1.82
CH	-0.22	-0.19	0.49	0.04	-0.19	0.14	-0.28	-0.29	0.29	0.05	0.22	0.10
	-0.68	-0.62	1.43	0.14	-0.63	0.49	-0.96	-0.91	0.89	0.16	0.70	0.27
FR	-0.24	0.77	0.09	-0.01	0.59	-0.07	-0.05	0.46	0.22	0.03	0.40	0.31
	-0.78	2.64	0.23	-0.03	1.97	-0.23	-0.16	1.41	0.64	0.09	1.43	0.85
IL	0.80	0.52	0.13	0.53	0.59	0.66	0.80	0.46	-0.11	0.83	0.75	0.02
	2.31	1.25	0.26	1.36	1.72	1.51	2.42	1.23	-0.23	2.12	2.09	0.04
ES	0.05	0.69	-0.03	0.39	0.27	0.49	-0.23	0.43	0.06	0.79	-0.37	0.20
	0.11	1.65	-0.08	0.95	0.66	1.28	-0.51	0.98	0.16	1.98	-0.89	0.50
NL	0.30	0.31	1.39	0.19	0.79	1.10	0.33	0.77	0.92	0.93	0.54	0.64
	0.64	0.67	3.74	0.39	2.07	2.96	0.71	1.85	2.54	1.98	1.42	1.48
SWE	0.27	1.02	1.14	0.36	0.58	1.12	0.47	0.74	1.57	0.37	0.67	0.73
	0.59	1.94	1.80	0.71	1.09	2.19	1.08	1.30	2.52	0.83	1.28	1.25
DK	0.46	0.15	0.14	0.66	-0.17	0.69	0.40	0.19	-0.38	0.35	0.38	-0.30
	1.38	0.31	0.29	1.74	-0.41	1.21	1.13	0.43	-0.67	1.03	0.97	-0.59
# max	2	3	6	2	2	7	2	2	7	4	3	4
ranking	2.55	1.73	1.73	2.18	2.36	1.45	2.55	1.91	1.55	2.00	2.18	1.82

Across most countries and liquidity metrics the general pattern is that the largest dispersion effects occur for the least liquid stocks and that profitability is increasing with illiquidty. For instance, the U.S. dispersion effect is only significant for the least liquid stocks—measuring liquidity by dollar volume or *ILLIQ*. Using share turnover or the measure of Liu (2006) the dispersion strategy's profitability behaves differently.

The pattern of profitability decreasing with liquidity can also be observed for the aggregate European strategy. Judging by dollar volume, share turnover and *ILLIQ* the strategy is only useless among the most illiquid stocks while the other buckets do show similar returns. While most of the country-level results comply with this liquidity-profitability relationship Italy is the odd one out since the dispersion strategy is only profitable among the most liquid stocks—regardless of the liquidity measure. Nevertheless, among the six naïvely derived significant dispersion effects we find five to be significantly affected by liquidity issues. Given that illiquidity is a common proxy for financial distress our results complement the finding of Avramov, Chordia, Jostova, and Philipov (2008) that the U.S. dispersion effect is confined to the worst rated companies. All in all, this evidence questions the successful implementation of any examined dispersion effect.

Chapter 7

Conclusion

The investigation of a given security mispricing typically addresses two questions: Is the anomaly simply a compensation for risk or is the anomaly real and, if yes, what behavioral bias is driving it? Of course, these questions are only meaningful if the security mispricing is not spurious in the first place. Hence, one needs to safeguard against data snooping biases.

We first demonstrate the importance of multiple testing issues in the case of the global accrual anomaly. For this anomaly to exist, we must be able to find statistical evidence for abnormal returns generated by a trading rule that goes short in the highest accrual quintile and long in the lowest quintile. For the U.S., a growing body of empirical research reports the accrual anomaly. Recent studies have also documented anomalous returns from this hedge strategy in other developed equity markets. We have raised the concern that these studies do not account for the multitude of tests involved. Without adjusting for multiple hypotheses testing, we confirm the global accrual anomaly patterns uncovered in prior studies. Only some of the hedge strategies do show promising performance in terms of risk-adjusted return. Controlling for common risk factors in an extended Fama-French model, we see that only a small number of markets provide returns that are both statistically and economically significant.

Given the abnormal return of hedge strategies in some countries, one may still feel that they might have happened by chance alone. Therefore, we examine our results as to their robustness to multiple testing. To be fair, we use the recent proposals of Romano and Wolf (2005) and Romano, Shaikh, and Wolf (2008). They are more powerful than previous suggestions in the literature and, therefore, true anomalies have a better chance to actually manifest. While international momentum strategies are robust to this battery of tests, few of the risk-adjusted returns from accrual-based hedge strategies continue to be anomalous in this more appropriate setting. Besides offering potential explanations as to why the accrual anomaly may be specific to the detected countries, we document that the returns to the associated hedge strategy are diminishing in recent times. Regardless of the anomaly's true nature, statistical fluke or actual mispricing, the decrease in returns may indicate that investors seek to benefit from Sloan's (1996) initial study, eventually rendering the associated trading strategy useless.

Discovering that both price and earnings momentum are robust with respect to multiple testing issues, we reinforce the growing body of research documenting magnitude and persistence of both anomalies. Researchers have long been speculating about a link between price and earnings momentum. Inspired by the work of Chordia and Shivakumar (2006), we find that European price momentum most likely is subsumed by earnings momentum. However, there are some European countries that do not support such a conclusion. As for the U.S., we especially observe some decoupling of price and earnings momentum following the burst of the tech bubble. In any case, our findings suggest that the price momentum rationale will most likely be related to earnings momentum. Given that momentum does not appear to proxy for macroeconomic risk, we narrow the search in favor of a behavioral-based explanation of the momentum anomaly. In particular, winner and loser portfolios characterized by high information uncertainty give rise to even larger momentum profits. Thus, given that price momentum largely is earnings momentum in disguise, our evidence supports the rationale of momentum being driven by investors' underreaction to fundamental news. Moreover, we attribute the persistence of the momentum anomaly to the fact that significant arbitrage costs prevent investors from its exploitation. Also, liquidity is a crucial driver in governing the momentum effects. However, while the U.S. momentum effects clearly are most pronounced among illiquid winner and loser stocks, there are some European markets that exhibit very profitable momentum strategies even for highly liquid stocks. Especially, the momentum strategies designed for the aggregate European sample appear quite robust.

Finally, we find that the dispersion effect does not prevail when subjected to multiple testing controls. This startling finding is resolved by examining the time series evolution of the international dispersion effects. Most of the associated returns amass in a rather narrow time frame of 3 years. Moreover, we find the dispersion effect to be most pronounced among high and low dispersion portfolios characterized by high information uncertainty. Since the dispersion effect is especially pronounced when limited to high idiosyncratic risk or highly illiquid stocks, we further corroborate that high arbitrage costs additionally deter investors from its exploitation.

To conclude, accounting for data snooping biases in global market anomalies provides a fresh view when assessing capital market efficiency. Ex ante, we expect this paradigm shift to lead to fewer statistically significant anomalies, however, even if an anomaly is deemed to be robust with respect to data snooping biases there are some important economic issues to be considered. As for the accrual anomaly we document that the anomalous patterns in the U.S. and the U.K. have been exploited by investors following their publication. While investors' learning has rendered markets efficient with respect to accruals mispricing it is all the more surprising why the momentum effect is not being taken advantage of. We evidence that arbitraging momentum is simply too costly, especially, it appears that our common factor controls are missing an important factor, namely liquidity risk. The latter also significantly affects the dispersion strategy which would have additionally required implementing rather infeasible positions. Taken together, we have gathered considerable evidence that global equity markets are more efficient than they appear by revealing many anomalies to be more apparent than real.

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